MachineLearning

2st Assignment - Shahid Beheshti University April 18, 2023

Outline

Packages

In [1]:
```
import numpy as np
import pandas as pd
import random
#plotting packages
import matplotlib.pyplot as plt
from matplotlib import pyplot
from matplotlib.pyplot import figure
import seaborn as sns
#splitting data to train and test
from sklearn.model_selection import train_test_split
from scipy import stats
#Models
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn import tree
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from xgboost import XGBClassifier
from sklearn.ensemble import GradientBoostingClassifier
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.feature_selection import SelectFromModel
#model selection
from sklearn.model_selection import GridSearchCV
#metrics
from statistics import mean, stdev
import math
from sklearn.metrics import classification_report
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
from sklearn.metrics import precision_score
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import confusion_matrix
from sklearn.metrics import f1_score
from sklearn.metrics import roc_curve
from sklearn.metrics import roc_auc_score
#wrapper methods
from mlxtend.feature_selection import SequentialFeatureSelector as SFS
#filter methods feature selection
from sklearn.feature_selection import chi2
from sklearn import preprocessing
from sklearn.feature_selection import mutual_info_classif
import shap
from scipy.stats import chisquare
from sklearn.feature_selection import r_regression, SelectKBest,SelectPercentile,f_regression
from sklearn.decomposition import PCA
from sklearn.ensemble import RandomForestRegressor
from sklearn.inspection import permutation_importance
#clustering
from sklearn.cluster import KMeans
#multicollinearity
from statsmodels.stats.outliers_influence import variance_inflation_factor
from statsmodels.tools.tools import add_constant
#binning
from scipy.stats import binned_statistic
#Encoding
from sklearn.preprocessing import OrdinalEncoder
#Treat imbalanced target
from imblearn.under_sampling import TomekLinks
from imblearn.over_sampling import SMOTE
from sklearn.utils.class_weight import compute_class_weight
#cross validation
from sklearn.model_selection import train_test_split, StratifiedKFold, StratifiedShuffleSplit, KFold
from sklearn.model_selection import RepeatedStratifiedKFold
#extra
from sklearn.ensemble import RandomForestRegressor, GradientBoostingRegressor
#15
from sklearn.base import BaseEstimator, ClassifierMixin
from sklearn.utils import resample
from sklearn.preprocessing import LabelEncoder

#Larger dataframe
pd.set_option('display.max_columns', 500)
pd.set_option('max_colwidth', None)
```

Exercise 13

In this part, you are going to work with the Vehicle Insurance Claim Fraud Detection dataset. You will implement multiple classification models using the Scikit-Learn package to predict if a claim application is fraudulent or not, based on about 32 features

Outline

Using these classes to test our models

Methods

Models

In [2]:
```
class Models():

    def __init__(self, dataset, target):
        self.dataset = dataset
        self.target = target
        self.X = self.dataset[dataset.columns.difference([self.target])]
        self.Y = self.dataset[self.target]
        self.X_train, self.X_test, self.Y_train, self.Y_test = train_test_split(self.X, self.Y,
                                                                                test_size = 1/5, random_state = 0 )
        self.dictAccuracy = {}
        self.dictF1       = {}



    #Method for display confusion matrix and ROC a AUC
    def confusionMat(self, Y_test, y_pred,y_prob):
        cf_matrix = confusion_matrix(Y_test, y_pred)
        group_names = ['True Neg','False Pos','False Neg','True Pos']
        group_counts = ["{0:0.0f}".format(value) for value in
                        cf_matrix.flatten()]
        group_percentages = ["{0:.2%}".format(value) for value in
                             cf_matrix.flatten()/np.sum(cf_matrix)]

        labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
                  zip(group_names,group_counts,group_percentages)]
        labels = np.asarray(labels).reshape(2,2)
        fpr, tpr, thresh = roc_curve(Y_test, y_prob, pos_label=1)
        auc = roc_auc_score(Y_test, y_prob)
        fig, ax = plt.subplots(1, 2, figsize=(20, 8))
        sns.heatmap(cf_matrix, annot=labels, fmt="", cmap='Blues',ax=ax[0])
        plt.plot(fpr,tpr,label="AUC="+str(auc))
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.legend(loc=4)
        plt.show()

    #Logistic

    def Logistic(self):
        logreg = LogisticRegression(random_state=16, max_iter=1000)
        logreg.fit(self.X_train, self.Y_train)
        y_pred = logreg.predict(self.X_test)
        y_prob = logreg.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        print("\nLogisticRegression.....................................\n")
        print("Accuracy:", accuracy)
        self.dictAccuracy['LogisticRegression'] = accuracy
        print("F1-Score:", f1)
        self.dictF1['LogisticRegression'] = f1
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames,zero_division=1))

    #Decison Tree
    def DT(self,plt):
        dtc = DecisionTreeClassifier()
        dtc.fit(self.X_train, self.Y_train)
        y_pred = dtc.predict(self.X_test)
        y_prob = dtc.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['DecisionTree'] = accuracy
        self.dictF1['DecisionTree'] = f1
        print("\nDecisionTree.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))
        dtc.feature_importances_
        if plt:
            self.decisonFeature(self.dataset.columns.difference([target])
                                ,dtc.feature_importances_ )



    #Random forest
    def RF(self):
        rf = RandomForestClassifier(n_estimators=500, random_state=42)
        rf.fit(self.X_train, self.Y_train)
        y_pred = rf.predict(self.X_test)
        y_prob = rf.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['Random forest'] = accuracy
        self.dictF1['Random forest'] = f1
        print("\nRandomForest.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))

    #KNN
    def KNN(self):
        knn = KNeighborsClassifier()
        knn.fit(self.X_train, self.Y_train)
        y_pred = knn.predict(self.X_test)
        y_prob = knn.predict_proba(self.X_test)[:, 1]

        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['KNN'] = accuracy
        self.dictF1['KNN'] = f1
        print("\nKNN.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", str(f1))
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))

    #SVC
    def SVC(self):
        clf = SVC(kernel='linear', probability=True)
        clf.fit(self.X_train,self.Y_train)
        y_pred = clf.predict(self.X_test)
        y_prob = clf.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['SVC'] = accuracy
        self.dictF1['SVC'] = f1
        print("\nSVC.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames , zero_division=1))
```

```
    #Metric Table
    def table(self):
        self.dictF1 = sorted(self.dictF1.items(), key=lambda x:x[1],reverse=True)
        self.dictAccuracy = sorted(self.dictAccuracy.items(), key=lambda x:x[1] ,reverse=True)
        acc = pd.DataFrame.from_dict(self.dictAccuracy)
        f1 = pd.DataFrame.from_dict(self.dictF1)

        print("\nF1-Score.....................................\n")
        print(f1)

        print("\nAccuracy.....................................\n")
        print(acc)

    #Feature importance
    def decisonFeature(self ,features ,importances ):
        print("\nFeature Importance.....................................\n")
        wid = len(features)
        print(len(features), len(importances))
        print(wid)
        figure(figsize=(20,wid))
        sorted_idx = importances.argsort()
        print(features[sorted_idx])
        plt.barh(features[sorted_idx], importances[sorted_idx])
        plt.show()


    def ROC_AUC(self,Y_test,y_pred):
        fpr, tpr, thresh = roc_curve(Y_test, y_pred, pos_label=1)
        plt.figure(figsize=(8,5))
        plt.plot(fpr,tpr)
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.show()
    #Output
    def testClassification(self):
        self.Logistic()
        self.DT(False)
        self.RF()
        self.KNN()
        self.SVC()
        self.table()
```

EDA Methods

In [3]:
```
def featureAnalysis(feature,dataset):
    a = dataset.describe()
    b = a[feature].to_frame().T
    fig, ax = plt.subplots(2, 1, figsize=(20, 18))
    sns.histplot(x=dataset[feature], data=dataset, kde=True, element="step",ax=ax[0])
    sns.boxplot(data=dataset , x = feature ,ax=ax[1])
    return(b)
```

Load Dataset

In [4]:
```
dataset = pd.read_csv('dataset/fraud_oracle.csv')
```

In [5]:
```
dataset.shape
```

Out[5]:
```
(15420, 33)
```

In [6]:
```
target = 'FraudFound_P'
```

In [7]:
```
dataset
```

Out[7]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Sex	MaritalStatus	Age	Fault	PolicyType	VehicleCategory	VehiclePrice	FraudFound_P	PolicyNumber	RepNumber	Deductible	DriverRating	Days_Policy_Accident	Days_Policy_Claim	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	PoliceReportFiled	WitnessPresent	AgentType	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	Year	BasePol
0	Dec	5	Wednesday	Honda	Urban	Tuesday	Jan	1	Female	Single	21	Policy Holder	Sport - Liability	Sport	more than 69000	0	1	12	300	1	more than 30	more than 30	none	3 years	26 to 30	No	No	External	none	1 year	3 to 4	1994	Liabi
1	Jan	3	Wednesday	Honda	Urban	Monday	Jan	4	Male	Single	34	Policy Holder	Sport - Collision	Sport	more than 69000	0	2	15	400	4	more than 30	more than 30	none	6 years	31 to 35	Yes	No	External	none	no change	1 vehicle	1994	Collis
2	Oct	5	Friday	Honda	Urban	Thursday	Nov	2	Male	Married	47	Policy Holder	Sport - Collision	Sport	more than 69000	0	3	7	400	3	more than 30	more than 30	1	7 years	41 to 50	No	No	External	none	no change	1 vehicle	1994	Collis
3	Jun	2	Saturday	Toyota	Rural	Friday	Jul	1	Male	Married	65	Third Party	Sedan - Liability	Sport	20000 to 29000	0	4	4	400	2	more than 30	more than 30	1	more than 7	51 to 65	Yes	No	External	more than 5	no change	1 vehicle	1994	Liabi
4	Jan	5	Monday	Honda	Urban	Tuesday	Feb	2	Female	Single	27	Third Party	Sport - Collision	Sport	more than 69000	0	5	3	400	1	more than 30	more than 30	none	5 years	31 to 35	No	No	External	none	no change	1 vehicle	1994	Collis
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	
15415	Nov	4	Friday	Toyota	Urban	Tuesday	Nov	5	Male	Married	35	Policy Holder	Sedan - Collision	Sedan	20000 to 29000	1	15416	5	400	4	more than 30	more than 30	2 to 4	6 years	31 to 35	No	No	External	none	no change	1 vehicle	1996	Collis
15416	Nov	5	Thursday	Pontiac	Urban	Friday	Dec	1	Male	Married	30	Policy Holder	Sedan - Liability	Sport	30000 to 39000	0	15417	11	400	3	more than 30	more than 30	more than 4	6 years	31 to 35	No	No	External	more than 5	no change	3 to 4	1996	Liabi
15417	Nov	5	Thursday	Toyota	Rural	Friday	Dec	1	Male	Single	24	Policy Holder	Sedan - Collision	Sedan	20000 to 29000	1	15418	4	400	4	more than 30	more than 30	more than 4	5 years	26 to 30	No	No	External	1 to 2	no change	1 vehicle	1996	Collis
15418	Dec	1	Monday	Toyota	Urban	Thursday	Dec	2	Female	Married	34	Third Party	Sedan - All Perils	Sedan	20000 to 29000	0	15419	6	400	4	more than 30	more than 30	none	2 years	31 to 35	No	No	External	more than 5	no change	1 vehicle	1996	All Pe
15419	Dec	2	Wednesday	Toyota	Urban	Thursday	Dec	3	Male	Single	21	Policy Holder	Sedan - Collision	Sedan	20000 to 29000	1	15420	3	400	4	more than 30	more than 30	none	5 years	26 to 30	No	No	External	1 to 2	no change	1 vehicle	1996	Collis

15420 rows × 33 columns

In [8]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 15420 entries, 0 to 15419
Data columns (total 33 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Month                 15420 non-null  object
 1   WeekOfMonth           15420 non-null  int64
 2   DayOfWeek             15420 non-null  object
 3   Make                  15420 non-null  object
 4   AccidentArea          15420 non-null  object
 5   DayOfWeekClaimed      15420 non-null  object
 6   MonthClaimed          15420 non-null  object
 7   WeekOfMonthClaimed    15420 non-null  int64
 8   Sex                   15420 non-null  object
 9   MaritalStatus         15420 non-null  object
 10  Age                   15420 non-null  int64
 11  Fault                 15420 non-null  object
 12  PolicyType            15420 non-null  object
 13  VehicleCategory       15420 non-null  object
 14  VehiclePrice          15420 non-null  object
 15  FraudFound_P          15420 non-null  int64
 16  PolicyNumber          15420 non-null  int64
 17  RepNumber             15420 non-null  int64
 18  Deductible            15420 non-null  int64
 19  DriverRating          15420 non-null  int64
 20  Days_Policy_Accident  15420 non-null  object
 21  Days_Policy_Claim     15420 non-null  object
 22  PastNumberOfClaims    15420 non-null  object
 23  AgeOfVehicle          15420 non-null  object
 24  AgeOfPolicyHolder     15420 non-null  object
 25  PoliceReportFiled     15420 non-null  object
 26  WitnessPresent        15420 non-null  object
 27  AgentType             15420 non-null  object
 28  NumberOfSuppliments   15420 non-null  object
 29  AddressChange_Claim   15420 non-null  object
 30  NumberOfCars          15420 non-null  object
 31  Year                  15420 non-null  int64
 32  BasePolicy            15420 non-null  object
dtypes: int64(9), object(24)
memory usage: 3.9+ MB
```

In [9]:
```
#No null values
#String 22
#Integer 9
#BooLean 2
```

In [10]:
```
dataset=dataset.drop_duplicates()
dataset.shape
```

Out[10]:
```
(15420, 33)
```

In [11]:
```
#No duplicated value
```

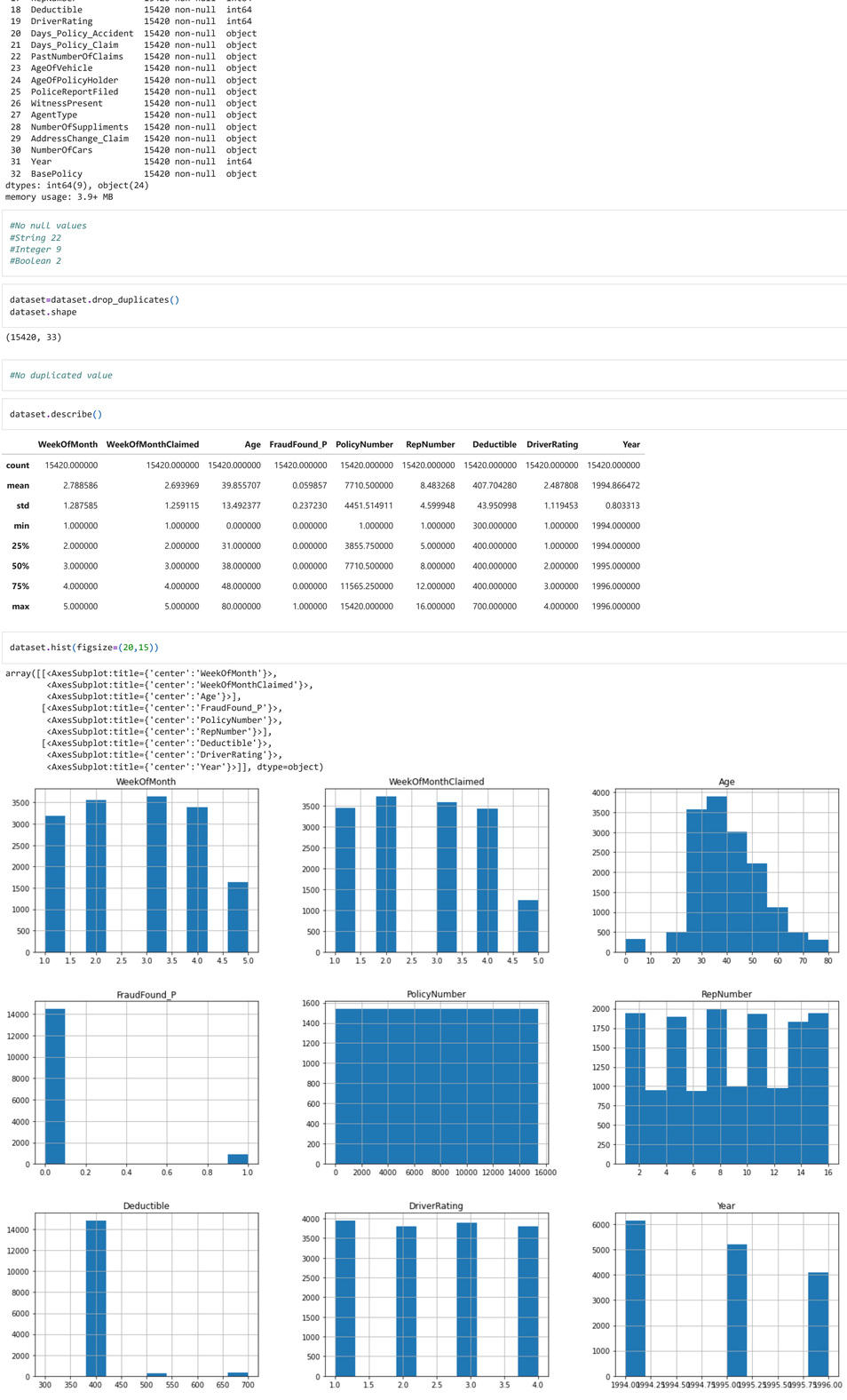
In [12]:
```
dataset.describe()
```

Out[12]:

	WeekOfMonth	WeekOfMonthClaimed	Age	FraudFound_P	PolicyNumber	RepNumber	Deductible	DriverRating	Year
count	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000	15420.000000
mean	2.788586	2.693969	39.855707	0.059857	7710.500000	8.483268	407.704280	2.487808	1994.866472
std	1.287585	1.259115	13.492377	0.237230	4451.514911	4.599948	43.950998	1.119453	0.803313
min	1.000000	1.000000	0.000000	0.000000	1.000000	1.000000	300.000000	1.000000	1994.000000
25%	2.000000	2.000000	31.000000	0.000000	3855.750000	5.000000	400.000000	1.000000	1994.000000
50%	3.000000	3.000000	38.000000	0.000000	7710.500000	8.000000	400.000000	2.000000	1995.000000
75%	4.000000	4.000000	48.000000	0.000000	11565.250000	12.000000	400.000000	3.000000	1996.000000
max	5.000000	5.000000	80.000000	1.000000	15420.000000	16.000000	700.000000	4.000000	1996.000000

In [13]:
```
dataset.hist(figsize=(20,15))
```

Out[13]:
```
array([[<AxesSubplot:title={'center':'WeekOfMonth'}>,
        <AxesSubplot:title={'center':'WeekOfMonthClaimed'}>,
        <AxesSubplot:title={'center':'Age'}>],
       [<AxesSubplot:title={'center':'FraudFound_P'}>,
        <AxesSubplot:title={'center':'PolicyNumber'}>,
        <AxesSubplot:title={'center':'RepNumber'}>],
       [<AxesSubplot:title={'center':'Deductible'}>,
        <AxesSubplot:title={'center':'DriverRating'}>,
        <AxesSubplot:title={'center':'Year'}>]], dtype=object)
```



In [14]:
```
dataset['PolicyNumber']
```

Out[14]:
```
0            1
1            2
2            3
3            4
4            5
         ...
15415    15416
15416    15417
15417    15418
15418    15419
15419    15420
Name: PolicyNumber, Length: 15420, dtype: int64
```

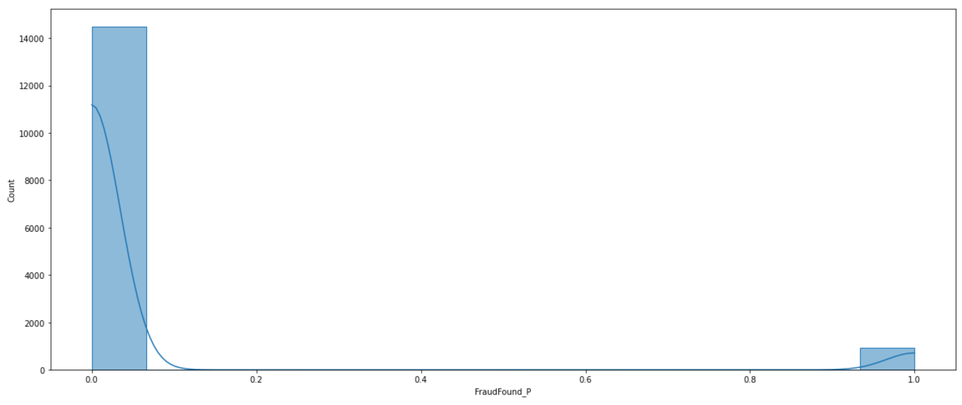
In [15]:
```
dataset.drop('PolicyNumber', inplace=True, axis=1)
```

Let's check target specifcly

In [16]:
```
featureAnalysis('FraudFound_P',dataset)
```

Out[16]:

	count	mean	std	min	25%	50%	75%	max
FraudFound_P	15420.0	0.059857	0.23723	0.0	0.0	0.0	0.0	1.0



Over 95 percent of our target is labeled as zero so Imbalanced dataset

In [17]:
```
dataset[dataset['FraudFound_P'] == 0]['FraudFound_P'].count() / dataset.shape[0]
```

Out[17]:
```
0.9401426718547341
```

In [18]:
```
orginal = dataset.copy()
```

Handle Categorical Features

First we should seperate nominal and ordinal

In [19]:
```
category = dataset.select_dtypes(include=['object']).columns.tolist()
category
```

Out[19]:
```
['Month',
 'DayOfWeek',
 'Make',
 'AccidentArea',
 'DayOfWeekClaimed',
 'MonthClaimed',
 'Sex',
 'MaritalStatus',
 'Fault',
 'PolicyType',
 'VehicleCategory',
 'VehiclePrice',
 'Days_Policy_Accident',
 'Days_Policy_Claim',
 'PastNumberOfClaims',
 'AgeOfVehicle',
 'AgeOfPolicyHolder',
 'PoliceReportFiled',
 'WitnessPresent',
 'AgentType',
 'NumberOfSuppliments',
 'AddressChange_Claim',
 'NumberOfCars',
 'BasePolicy']
```

In [20]:
```
ordinal = ['Month','DayOfWeek','DayOfWeekClaimed','MonthClaimed'
           ,'VehiclePrice','Days_Policy_Accident','Days_Policy_Claim','PastNumberOfClaims','AgeOfVehicle'
           ,'AgeOfPolicyHolder','NumberOfSuppliments','AddressChange_Claim','NumberOfCars']
```

In [21]:
```
setCat = set(category)
nominal = setCat.difference(ordinal)
nominal
```

Out[21]:
```
{'AccidentArea',
 'AgentType',
 'BasePolicy',
 'Fault',
 'Make',
 'MaritalStatus',
 'PoliceReportFiled',
 'PolicyType',
 'Sex',
 'VehicleCategory',
 'WitnessPresent'}
```

Using ordinal encoding for ordinal features

In [22]:
```
len(orginal['AgeOfPolicyHolder'].unique())
```

Out[22]:
```
9
```

In [23]:
```
orginal['AgeOfVehicle'].unique()
```

Out[23]:
```
array(['3 years', '6 years', '7 years', 'more than 7', '5 years', 'new',
       '4 years', '2 years'], dtype=object)
```

In [24]:
```
map_month = {"Jan":0, "Feb":1, "Mar":2 ,
             "Apr":3, "May":4, "Jun":5,
             "Jul":6, "Aug":7, "Sep":8,
             "Oct":9, "Nov":10, "Dec":11}

map_day      = {"Sunday":0, "Monday":1, "Tuesday":2 ,
                "Thursday":3, "Wednesday":4, "Friday":5,
                "Saturday":6}
#start from one
map_price    = {"less than 20000":1, "20000 to 29000":2, "30000 to 39000":3 ,
                "40000 to 59000" :4, "60000 to 69000":5, "more than 69000":6}

map_dayAcc   = {"none":0, "1 to 7":1, "8 to 15":2 ,
                "15 to 30":3, "more than 30":4}

map_dayClaim = {"none":0,  "8 to 15":1 ,"15 to 30":2, "more than 30":3}

map_postNUm  = {"none":0,  "1":1 ,"2 to 4":2, "more than 4":3}

map_age      = {"new":1,  "2 years":2 ,"3 years":3,
                "4 years":4, "5 years":5, "6 years":6,
                "7 years":7, "more than 7":9}

map_agePol      = {"16 to 17":1 ,  "18 to 20":2 ,"21 to 25":4,
                "26 to 30":5  ,  "31 to 35":6  , "36 to 40":7,
                "41 to 50":10  ,  "51 to 65":15 , "over 65":20}

map_Supp = {"none":0,  "1 to 2":1 ,"3 to 5":2, "more than 5":3}
#Not equal gap between
map_add =  { "no change":0, "under 6 months":1 ,"1 year":2 ,"2 to 3 years":3, "4 to 8 years":5}

map_cars = {"1 vehicle":1, "2 vehicles":2 ,"3 to 4":3.5 ,"5 to 8":6.5, "more than 8":10}
```

In [25]:
```
dataset['Month']=dataset.Month.map(map_month)
dataset['DayOfWeek']=dataset.DayOfWeek.map(map_day)
dataset['DayOfWeekClaimed']=dataset.DayOfWeekClaimed.map(map_day)
dataset['MonthClaimed']=dataset.MonthClaimed.map(map_month)
dataset['VehiclePrice']=dataset.VehiclePrice.map(map_price)
dataset['Days_Policy_Accident']=dataset.Days_Policy_Accident.map(map_dayAcc)
dataset['Days_Policy_Claim']=dataset.Days_Policy_Claim.map(map_dayClaim)
dataset['PastNumberOfClaims']=dataset.PastNumberOfClaims.map(map_postNUm)
dataset['AgeOfVehicle']=dataset.AgeOfVehicle.map(map_age)
dataset['AgeOfPolicyHolder']=dataset.AgeOfPolicyHolder.map(map_agePol)
dataset['NumberOfSuppliments']=dataset.NumberOfSuppliments.map(map_Supp)
dataset['AddressChange_Claim']=dataset.AddressChange_Claim.map(map_add)
dataset['NumberOfCars']=dataset.NumberOfCars.map(map_cars)
```

In [26]:
```
dataset
```

Out[26]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Sex	MaritalStatus	Age	Fault	PolicyType	VehicleCategory	VehiclePrice	FraudFound_P	RepNumber	Deductible	DriverRating	Days_Policy_Accident	Days_Policy_Claim	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	PoliceReportFiled	WitnessPresent	AgentType	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	Year	BasePolicy
0	11	5	4	Honda	Urban	2.0	0.0	1	Female	Single	21	Policy Holder	Sport - Liability	Sport	6	0	12	300	1	4	3	0	3	5	No	No	External	0	2	3.5	1994	Liability
1	0	3	4	Honda	Urban	1.0	0.0	4	Male	Single	34	Policy Holder	Sport - Collision	Sport	6	0	15	400	4	4	3	0	6	6	Yes	No	External	0	0	1.0	1994	Collision
2	9	5	5	Honda	Urban	3.0	10.0	2	Male	Married	47	Policy Holder	Sport - Collision	Sport	6	0	7	400	3	4	3	1	7	10	No	No	External	0	0	1.0	1994	Collision
3	5	2	6	Toyota	Rural	5.0	6.0	1	Male	Married	65	Third Party	Sedan - Liability	Sport	2	0	4	400	2	4	3	1	9	15	Yes	No	External	3	0	1.0	1994	Liability
4	0	5	1	Honda	Urban	2.0	1.0	2	Female	Single	27	Third Party	Sport - Collision	Sport	6	0	3	400	1	4	3	0	5	6	No	No	External	0	0	1.0	1994	Collision
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
15415	10	4	5	Toyota	Urban	2.0	10.0	5	Male	Married	35	Policy Holder	Sedan - Collision	Sedan	2	1	5	400	4	4	3	2	6	6	No	No	External	0	0	1.0	1996	Collision
15416	10	5	3	Pontiac	Urban	5.0	11.0	1	Male	Married	30	Policy Holder	Sedan - Liability	Sport	3	0	11	400	3	4	3	3	6	6	No	No	External	3	0	3.5	1996	Liability
15417	10	5	3	Toyota	Rural	5.0	11.0	1	Male	Single	24	Policy Holder	Sedan - Collision	Sedan	2	1	4	400	4	4	3	3	5	5	No	No	External	1	0	1.0	1996	Collision
15418	11	1	1	Toyota	Urban	3.0	11.0	2	Female	Married	34	Third Party	Sedan - All Perils	Sedan	2	0	6	400	4	4	3	0	2	6	No	No	External	3	0	1.0	1996	All Perils
15419	11	2	4	Toyota	Urban	3.0	11.0	3	Male	Single	21	Policy Holder	Sedan - Collision	Sedan	2	1	3	400	4	4	3	0	5	5	No	No	External	1	0	1.0	1996	Collision

15420 rows × 32 columns

In [27]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15420 entries, 0 to 15419
Data columns (total 32 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Month                 15420 non-null  int64
 1   WeekOfMonth           15420 non-null  int64
 2   DayOfWeek             15420 non-null  int64
 3   Make                  15420 non-null  object
 4   AccidentArea          15420 non-null  object
 5   DayOfWeekClaimed      15419 non-null  float64
 6   MonthClaimed          15419 non-null  float64
 7   WeekOfMonthClaimed    15420 non-null  int64
 8   Sex                   15420 non-null  object
 9   MaritalStatus         15420 non-null  object
 10  Age                   15420 non-null  int64
 11  Fault                 15420 non-null  object
 12  PolicyType            15420 non-null  object
 13  VehicleCategory       15420 non-null  object
 14  VehiclePrice          15420 non-null  int64
 15  FraudFound_P          15420 non-null  int64
 16  RepNumber             15420 non-null  int64
 17  Deductible            15420 non-null  int64
 18  DriverRating          15420 non-null  int64
```

```
 19  Days_Policy_Accident  15420 non-null  int64
 20  Days_Policy_Claim     15420 non-null  int64
 21  PastNumberOfClaims    15420 non-null  int64
 22  AgeOfVehicle          15420 non-null  int64
 23  AgeOfPolicyHolder     15420 non-null  int64
 24  PoliceReportFiled     15420 non-null  object
 25  WitnessPresent        15420 non-null  object
 26  AgentType             15420 non-null  object
 27  NumberOfSuppliments   15420 non-null  int64
 28  AddressChange_Claim   15420 non-null  int64
 29  NumberOfCars          15420 non-null  float64
 30  Year                  15420 non-null  int64
 31  BasePolicy            15420 non-null  object
dtypes: float64(3), int64(18), object(11)
memory usage: 4.4+ MB
```

In [28]:
```
dataset[dataset['DayOfWeekClaimed'].isnull()]
```

Out[28]:

	Month	WeekOfMonth	DayOfWeek	Make	AccidentArea	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Sex	MaritalStatus	Age	Fault	PolicyType	VehicleCategory	VehiclePrice	FraudFound_P	RepNumber	Deductible	DriverRating	Days_Policy_Accident	Days_Policy_Claim	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	PoliceReportFiled	WitnessPresent	AgentType	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	Year	BasePolicy
1516	6	2	1	Honda	Rural	NaN	NaN	1	Male	Single	0	Policy Holder	Sedan - All Perils	Sedan	6	0	15	400	2	4	0	0	1	1	No	No	External	0	0	1.0	1994	All Perils

In [29]:
```
orginal.loc[1516]
```

Out[29]:
```
Month                              Jul
WeekOfMonth                          2
DayOfWeek                       Monday
Make                             Honda
AccidentArea                     Rural
DayOfWeekClaimed                     0
MonthClaimed                         0
WeekOfMonthClaimed                   1
Sex                               Male
MaritalStatus                   Single
Age                                  0
Fault                      Policy Holder
PolicyType             Sedan - All Perils
VehicleCategory                  Sedan
VehiclePrice             more than 69000
FraudFound_P                         0
RepNumber                           15
Deductible                         400
DriverRating                         2
Days_Policy_Accident       more than 30
Days_Policy_Claim                none
PastNumberOfClaims               none
AgeOfVehicle                      new
AgeOfPolicyHolder           16 to 17
PoliceReportFiled                  No
WitnessPresent                     No
AgentType                    External
NumberOfSuppliments              none
AddressChange_Claim         no change
NumberOfCars                1 vehicle
Year                             1994
BasePolicy                 All Perils
Name: 1516, dtype: object
```

Set DayOfWeekClaimed and MonthClaimed to zero

In [30]:
```
dataset.loc[1516]
```

Out[30]:
```
Month                              6
WeekOfMonth                        2
DayOfWeek                          1
Make                           Honda
AccidentArea                   Rural
DayOfWeekClaimed                 NaN
MonthClaimed                     NaN
WeekOfMonthClaimed                 1
Sex                             Male
MaritalStatus                 Single
Age                                0
Fault                    Policy Holder
PolicyType           Sedan - All Perils
VehicleCategory                Sedan
VehiclePrice                       6
FraudFound_P                       0
RepNumber                         15
Deductible                       400
DriverRating                       2
Days_Policy_Accident               4
Days_Policy_Claim                  0
PastNumberOfClaims                 0
AgeOfVehicle                       1
AgeOfPolicyHolder                  1
PoliceReportFiled                 No
WitnessPresent                    No
AgentType                   External
NumberOfSuppliments                0
AddressChange_Claim                0
NumberOfCars                     1.0
Year                            1994
BasePolicy                 All Perils
Name: 1516, dtype: object
```

Drop it

In [31]:
```
dataset = dataset[dataset['DayOfWeekClaimed'].notnull()]
```

In [32]:
```
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15419 entries, 0 to 15419
Data columns (total 32 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Month                 15419 non-null  int64
 1   WeekOfMonth           15419 non-null  int64
 2   DayOfWeek             15419 non-null  int64
 3   Make                  15419 non-null  object
 4   AccidentArea          15419 non-null  object
 5   DayOfWeekClaimed      15419 non-null  float64
 6   MonthClaimed          15419 non-null  float64
 7   WeekOfMonthClaimed    15419 non-null  int64
 8   Sex                   15419 non-null  object
 9   MaritalStatus         15419 non-null  object
 10  Age                   15419 non-null  int64
 11  Fault                 15419 non-null  object
 12  PolicyType            15419 non-null  object
 13  VehicleCategory       15419 non-null  object
 14  VehiclePrice          15419 non-null  int64
 15  FraudFound_P          15419 non-null  int64
 16  RepNumber             15419 non-null  int64
 17  Deductible            15419 non-null  int64
 18  DriverRating          15419 non-null  int64
 19  Days_Policy_Accident  15419 non-null  int64
 20  Days_Policy_Claim     15419 non-null  int64
 21  PastNumberOfClaims    15419 non-null  int64
 22  AgeOfVehicle          15419 non-null  int64
 23  AgeOfPolicyHolder     15419 non-null  int64
 24  PoliceReportFiled     15419 non-null  object
 25  WitnessPresent        15419 non-null  object
 26  AgentType             15419 non-null  object
 27  NumberOfSuppliments   15419 non-null  int64
 28  AddressChange_Claim   15419 non-null  int64
 29  NumberOfCars          15419 non-null  float64
 30  Year                  15419 non-null  int64
 31  BasePolicy            15419 non-null  object
dtypes: float64(3), int64(18), object(11)
memory usage: 3.9+ MB
```

Using one-hat encoding for nominal features

In [33]:
```
dataset = pd.get_dummies(dataset, columns = nominal)
```

In [34]:
```
dataset
```

Out[34]:

	Month	WeekOfMonth	DayOfWeek	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Age	VehiclePrice	FraudFound_P	RepNumber	Deductible	DriverRating	Days_Policy_Accident	Days_Policy_Claim	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	Year	PoliceReportFiled_No	PoliceReportFiled_Yes	Fault_Policy Holder	Fault_Third Party	Make_Accura	Make_BMW	Make_Chevrolet	Make_Dodge	Make_Ferrari	Make_Forc
0	11	5	4	2.0	0.0	1	21	6	0	12	300	1	4	3	0	3	5	0	2	3.5	1994	1	0	1	0	0	0	0	0	0	0
1	0	3	4	1.0	0.0	4	34	6	0	15	400	4	4	3	0	6	6	0	0	1.0	1994	0	1	1	0	0	0	0	0	0	0
2	9	5	5	3.0	10.0	2	47	6	0	7	400	3	4	3	1	7	10	0	0	1.0	1994	1	0	1	0	0	0	0	0	0	0
3	5	2	6	5.0	6.0	1	65	2	0	4	400	2	4	3	1	9	15	3	0	1.0	1994	0	1	0	1	0	0	0	0	0	0
4	0	5	1	2.0	1.0	2	27	6	0	3	400	1	4	3	0	5	6	0	0	1.0	1994	1	0	0	1	0	0	0	0	0	0
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
15415	10	4	5	2.0	10.0	5	35	2	1	5	400	4	4	3	2	6	6	0	0	1.0	1996	1	0	1	0	0	0	0	0	0	0
15416	10	5	3	5.0	11.0	1	30	3	0	11	400	3	4	3	3	6	6	3	0	3.5	1996	1	0	1	0	0	0	0	0	0	0
15417	10	5	3	5.0	11.0	1	24	2	1	4	400	4	4	3	3	5	5	1	0	1.0	1996	1	0	1	0	0	0	0	0	0	0
15418	11	1	1	3.0	11.0	2	34	2	0	6	400	4	4	3	0	2	6	3	0	1.0	1996	1	0	0	1	0	0	0	0	0	0
15419	11	2	4	3.0	11.0	3	21	2	1	3	400	4	4	3	0	5	5	1	0	1.0	1996	1	0	1	0	0	0	0	0	0	0

15419 rows × 71 columns

In [35]:
```
dataset.info()
```

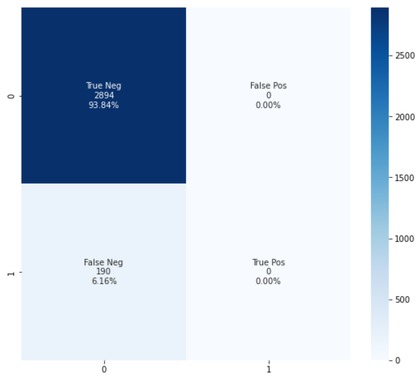
```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 15419 entries, 0 to 15419
Data columns (total 71 columns):
 #   Column                          Non-Null Count  Dtype
---  ------                          --------------  -----
 0   Month                           15419 non-null  int64
 1   WeekOfMonth                     15419 non-null  int64
 2   DayOfWeek                       15419 non-null  int64
 3   DayOfWeekClaimed                15419 non-null  float64
 4   MonthClaimed                    15419 non-null  float64
 5   WeekOfMonthClaimed              15419 non-null  int64
 6   Age                             15419 non-null  int64
 7   VehiclePrice                    15419 non-null  int64
 8   FraudFound_P                    15419 non-null  int64
 9   RepNumber                       15419 non-null  int64
 10  Deductible                      15419 non-null  int64
 11  DriverRating                    15419 non-null  int64
 12  Days_Policy_Accident            15419 non-null  int64
 13  Days_Policy_Claim               15419 non-null  int64
 14  PastNumberOfClaims              15419 non-null  int64
 15  AgeOfVehicle                    15419 non-null  int64
 16  AgeOfPolicyHolder               15419 non-null  int64
 17  NumberOfSuppliments             15419 non-null  int64
 18  AddressChange_Claim             15419 non-null  int64
 19  NumberOfCars                    15419 non-null  float64
 20  Year                            15419 non-null  int64
 21  PoliceReportFiled_No            15419 non-null  uint8
 22  PoliceReportFiled_Yes           15419 non-null  uint8
 23  Fault_Policy Holder             15419 non-null  uint8
 24  Fault_Third Party               15419 non-null  uint8
 25  Make_Accura                     15419 non-null  uint8
 26  Make_BMW                        15419 non-null  uint8
 27  Make_Chevrolet                  15419 non-null  uint8
 28  Make_Dodge                      15419 non-null  uint8
 29  Make_Ferrari                    15419 non-null  uint8
 30  Make_Ford                       15419 non-null  uint8
 31  Make_Honda                      15419 non-null  uint8
 32  Make_Jaguar                     15419 non-null  uint8
 33  Make_Lexus                      15419 non-null  uint8
 34  Make_Mazda                      15419 non-null  uint8
 35  Make_Mecedes                    15419 non-null  uint8
 36  Make_Mercury                    15419 non-null  uint8
 37  Make_Nisson                     15419 non-null  uint8
 38  Make_Pontiac                    15419 non-null  uint8
 39  Make_Porche                     15419 non-null  uint8
 40  Make_Saab                       15419 non-null  uint8
 41  Make_Saturn                     15419 non-null  uint8
 42  Make_Toyota                     15419 non-null  uint8
 43  Make_VW                         15419 non-null  uint8
 44  WitnessPresent_No               15419 non-null  uint8
 45  WitnessPresent_Yes              15419 non-null  uint8
 46  VehicleCategory_Sedan           15419 non-null  uint8
 47  VehicleCategory_Sport           15419 non-null  uint8
 48  VehicleCategory_Utility         15419 non-null  uint8
 49  BasePolicy_All Perils           15419 non-null  uint8
 50  BasePolicy_Collision            15419 non-null  uint8
 51  BasePolicy_Liability            15419 non-null  uint8
 52  PolicyType_Sedan - All Perils   15419 non-null  uint8
 53  PolicyType_Sedan - Collision    15419 non-null  uint8
 54  PolicyType_Sedan - Liability    15419 non-null  uint8
 55  PolicyType_Sport - All Perils   15419 non-null  uint8
 56  PolicyType_Sport - Collision    15419 non-null  uint8
 57  PolicyType_Sport - Liability    15419 non-null  uint8
 58  PolicyType_Utility - All Perils 15419 non-null  uint8
 59  PolicyType_Utility - Collision  15419 non-null  uint8
 60  PolicyType_Utility - Liability  15419 non-null  uint8
 61  AccidentArea_Rural              15419 non-null  uint8
 62  AccidentArea_Urban              15419 non-null  uint8
 63  Sex_Female                      15419 non-null  uint8
 64  Sex_Male                        15419 non-null  uint8
 65  MaritalStatus_Divorced          15419 non-null  uint8
 66  MaritalStatus_Married           15419 non-null  uint8
 67  MaritalStatus_Single            15419 non-null  uint8
 68  MaritalStatus_Widow             15419 non-null  uint8
 69  AgentType_External              15419 non-null  uint8
 70  AgentType_Internal              15419 non-null  uint8
dtypes: float64(3), int64(18), uint8(50)
memory usage: 3.3 MB
```

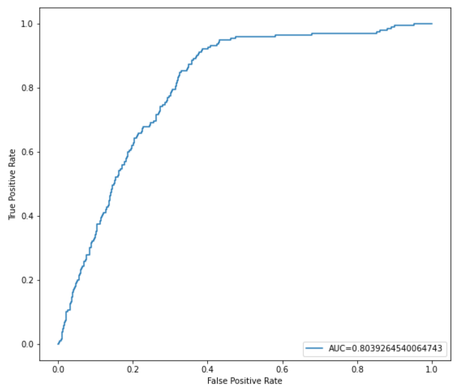
In [36]:
```
dataset_imbalanced = dataset.copy()
```

In [134…
```
model1 = Models(dataset,'FraudFound_P')
```

In [135…
```
model1.testClassification()
```

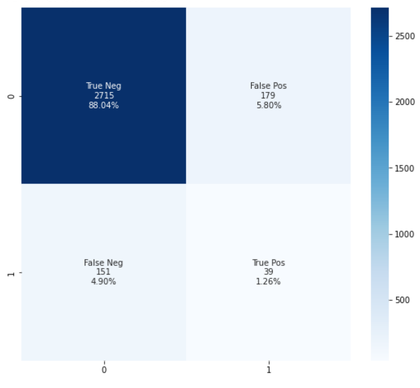
```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.................................

Accuracy: 0.9383916990920882
F1-Score: 0.0
```

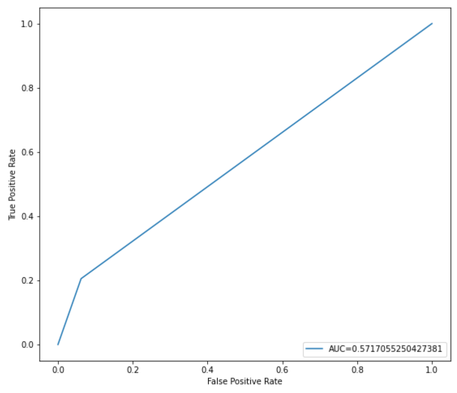




	precision	recall	f1-score	support
Yes	0.94	1.00	0.97	2894
No	1.00	0.00	0.00	190
accuracy			0.94	3084
macro avg	0.97	0.50	0.48	3084
weighted avg	0.94	0.94	0.91	3084

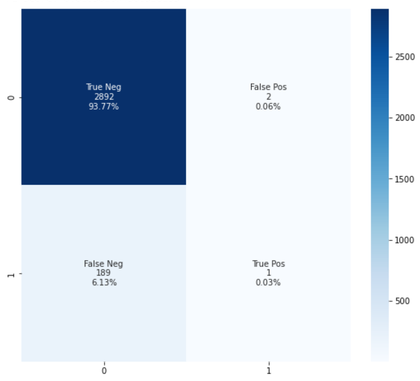
```
DecisionTree.......................................

Accuracy: 0.8929961089494164
F1-Score: 0.1911764705882353
```

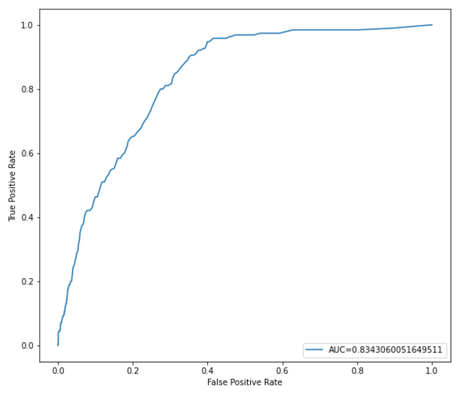




	precision	recall	f1-score	support
Yes	0.95	0.94	0.94	2894
No	0.18	0.21	0.19	190
accuracy			0.89	3084
macro avg	0.56	0.57	0.57	3084
weighted avg	0.90	0.89	0.90	3084

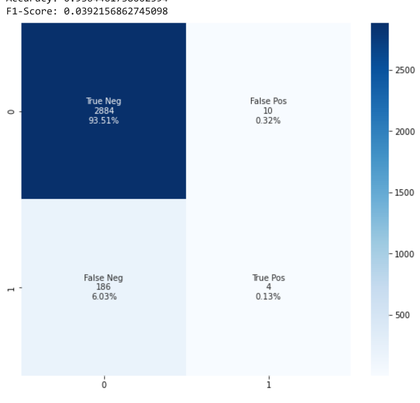
```
RandomForest.......................................

Accuracy: 0.9380674448767834
F1-Score: 0.010362694300518133
```

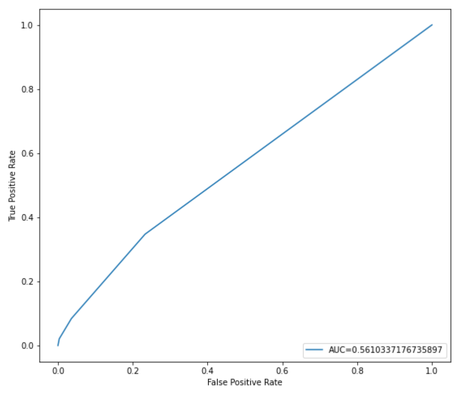




	precision	recall	f1-score	support
Yes	0.94	1.00	0.97	2894
No	0.33	0.01	0.01	190
accuracy			0.94	3084
macro avg	0.64	0.50	0.49	3084
weighted avg	0.90	0.94	0.91	3084

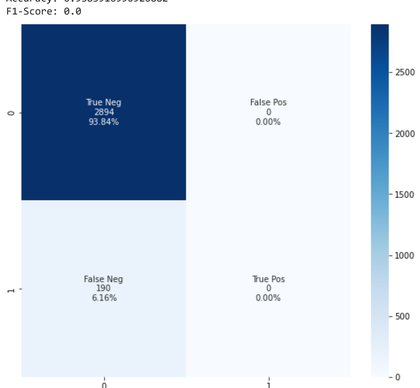
```
KNN................................................

Accuracy: 0.9364461738002594
F1-Score: 0.0392156862745098
```

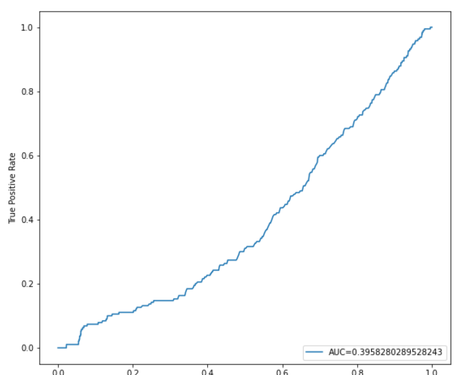




	precision	recall	f1-score	support
Yes	0.94	1.00	0.97	2894
No	0.29	0.02	0.04	190
accuracy			0.94	3084
macro avg	0.61	0.51	0.50	3084
weighted avg	0.90	0.94	0.91	3084

```
SVC................................................

Accuracy: 0.9383916990920882
F1-Score: 0.0
```





	precision	recall	f1-score	support
Yes	0.94	1.00	0.97	2894
No	1.00	0.00	0.00	190
accuracy			0.94	3084
macro avg	0.97	0.50	0.48	3084
weighted avg	0.94	0.94	0.91	3084

```
F1-Score...........................................

                   0         1
0       DecisionTree  0.191176
1                KNN  0.039216
2      Random forest  0.010363
3  LogisticRegression  0.000000
4                SVC  0.000000

Accuracy...........................................

                   0         1
0  LogisticRegression  0.938392
1                SVC  0.938392
2      Random forest  0.938067
3                KNN  0.936446
4       DecisionTree  0.892996
```

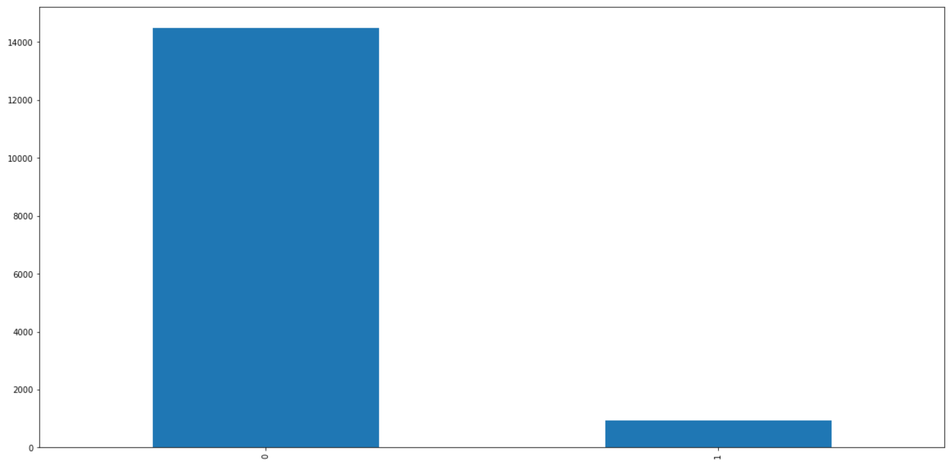
Getting high accuracy in all models(close to 90 percent) but is it really good? Absolutely not just look at the confusion matrix percentages.

The main reason behind this fake high score is the imbalanced target

We can find this out by looking f1score that is very close to zero

In [37]:
```
indpie = dataset_imbalanced['FraudFound_P'].value_counts()
indpie.plot(kind='bar',figsize=(20,10))
```

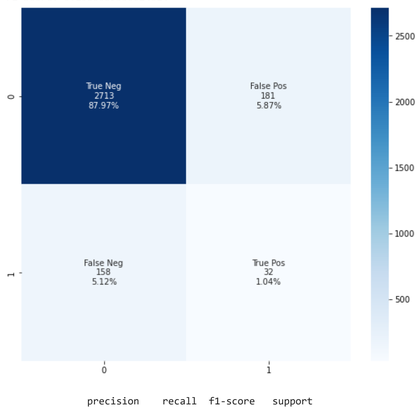
Out[37]:
```
<AxesSubplot:>
```

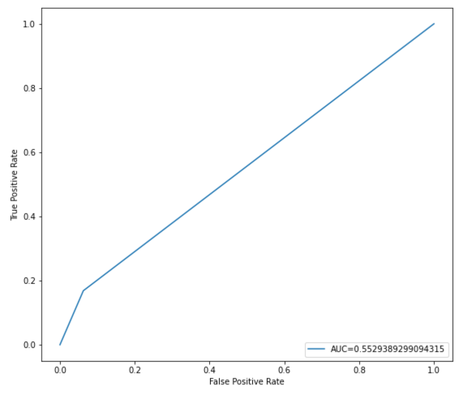


In [38]:
```
modelFeature = Models(dataset,'FraudFound_P')
```

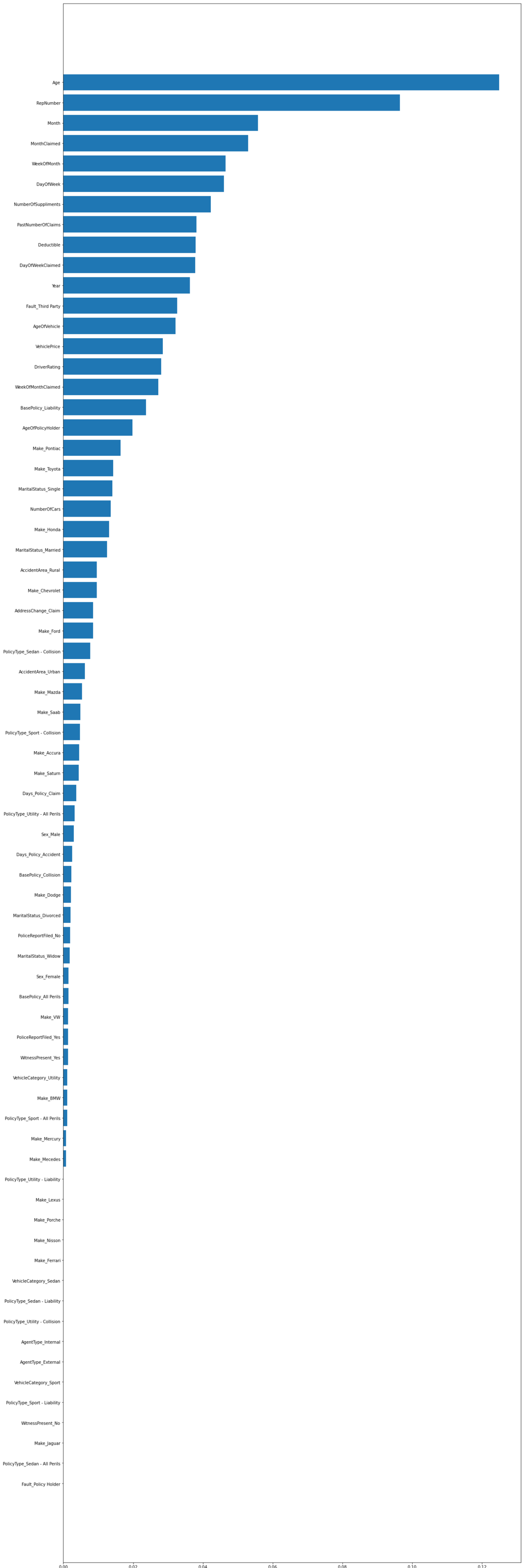
In [39]:
```
modelFeature.DT(True)
```

```
DecisionTree.....................................

Accuracy: 0.8900778210116731
F1-Score: 0.1588089330024814
```






```
              precision    recall  f1-score   support

         Yes       0.94      0.94      0.94      2894
          No       0.15      0.17      0.16       190

    accuracy                           0.89      3084
   macro avg       0.55      0.55      0.55      3084
weighted avg       0.90      0.89      0.89      3084


Feature Importance.................................

70 70
70
Index(['Fault_Policy Holder', 'PolicyType_Sedan - All Perils', 'Make_Jaguar',
       'WitnessPresent_No', 'PolicyType_Sport - Liability',
       'VehicleCategory_Sport', 'AgentType_External', 'AgentType_Internal',
       'PolicyType_Utility - Collision', 'PolicyType_Sedan - Liability',
       'VehicleCategory_Sedan', 'Make_Ferrari', 'Make_Nisson', 'Make_Porche',
       'Make_Lexus', 'PolicyType_Utility - Liability', 'Make_Mecedes',
       'Make_Mercury', 'PolicyType_Sport - All Perils', 'Make_BMW',
       'VehicleCategory_Utility', 'WitnessPresent_Yes',
       'PoliceReportFiled_Yes', 'Make_VW', 'BasePolicy_All Perils',
       'Sex_Female', 'MaritalStatus_Widow', 'PoliceReportFiled_No',
       'MaritalStatus_Divorced', 'Make_Dodge', 'BasePolicy_Collision',
       'Days_Policy_Accident', 'Sex_Male', 'PolicyType_Utility - All Perils',
       'Days_Policy_Claim', 'Make_Saturn', 'Make_Accura',
       'PolicyType_Sport - Collision', 'Make_Saab', 'Make_Mazda',
       'AccidentArea_Urban', 'PolicyType_Sedan - Collision', 'Make_Ford',
       'AddressChange_Claim', 'Make_Chevrolet', 'AccidentArea_Rural',
       'MaritalStatus_Married', 'Make_Honda', 'NumberOfCars',
       'MaritalStatus_Single', 'Make_Toyota', 'Make_Pontiac',
       'AgeOfPolicyHolder', 'BasePolicy_Liability', 'WeekOfMonthClaimed',
       'DriverRating', 'VehiclePrice', 'AgeOfVehicle', 'Fault_Third Party',
       'Year', 'DayOfWeekClaimed', 'Deductible', 'PastNumberOfClaims',
       'NumberOfSuppliments', 'DayOfWeek', 'WeekOfMonth', 'MonthClaimed',
       'Month', 'RepNumber', 'Age'],
      dtype='object')
```



Stratified kfold cross validation is typically useful when we have imbalanced data and where the data size is on the small side.

- Models
- Models_stratifed
- Models_sampling
- Models_weighted

Stratified cross-validation

In [40]:
```
class Models_Startified():

    def __init__(self, dataset, target,Ksplit):
        self.Ksplit = Ksplit
        self.dataset = dataset
        self.target = target
        self.X = self.dataset[dataset.columns.difference([self.target])]
        self.Y = self.dataset[self.target]
        self.X_train, self.X_test, self.Y_train, self.Y_test = train_test_split(self.X, self.Y,
                                                                                test_size = 1/5, random_state = 0 )

        self.dictAccuracy = {}
        self.dictF1       = {}
        self.skf = StratifiedKFold(n_splits=self.Ksplit, shuffle=True, random_state=1)


    def confusionMat(self, Y_test, y_pred,y_prob):
        cf_matrix = confusion_matrix(Y_test, y_pred)
        group_names = ['True Neg','False Pos','False Neg','True Pos']
        group_counts = ["{0:0.0f}".format(value) for value in
                        cf_matrix.flatten()]
        group_percentages = ["{0:.2%}".format(value) for value in
```

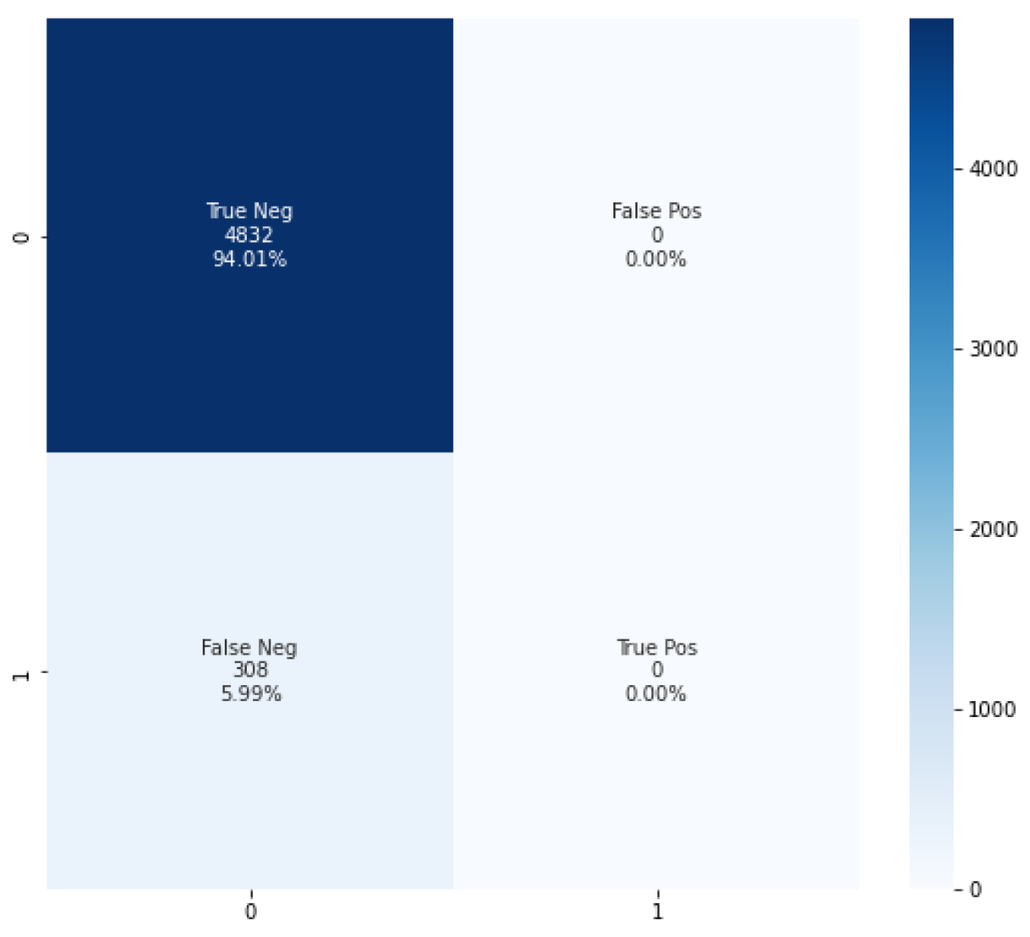
```
                        cf_matrix.flatten()/np.sum(cf_matrix)]

    labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    fpr, tpr, thresh = roc_curve(Y_test, y_prob, pos_label=1)
    auc = roc_auc_score(Y_test, y_prob)
    fig, ax = plt.subplots(1, 2, figsize=(20, 8))
    sns.heatmap(cf_matrix, annot=labels, fmt="", cmap='Blues',ax=ax[0])
    plt.plot(fpr,tpr,label="AUC="+str(auc))
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.legend(loc=4)
    plt.show()



def possibility_acc_f1(self,dictAcc,dictF1):
    print('List of possible accuracy:', dictAcc.values())
    print('\nMaximum Accuracy That can be obtained from this model is:',
          max(dictAcc.values())*100, '%')
    print('\nMinimum Accuracy:',
          min(dictAcc.values())*100, '%')
    print('\nOverall Accuracy:',
          mean(dictAcc.values())*100, '%')
    print('\nStandard Deviation is:', stdev(dictAcc.values()))
    print()
    print('List of possible F1-score:', dictF1.values())
    print('\nMaximum F1-score That can be obtained from this model is:',
          max(dictF1.values())*100, '%')
    print('\nMinimum F1-score:',
          min(dictF1.values())*100, '%')
    print('\nOverall F1-score:',
          mean(dictF1.values())*100, '%')
    print('\nStandard Deviation is:', stdev(dictF1.values()))
    print()


#Logistic
def Logistic(self):
    #Define dictionaries for possible folds
    log_accu_stratified = {}
    log_f1_stratified = {}
    Y_pred ={}
    Y_test ={}
    Y_prob = {}

    #Define Model
    logreg = LogisticRegression(random_state=16, max_iter=1000)
    n = 0
    for train_index, test_index in self.skf.split(self.X ,self.Y):
        n=n+1
        x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
        y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
        Y_test[n] = y_test_fold

        logreg.fit(x_train_fold, y_train_fold)
        y_prediction = logreg.predict(x_test_fold)
        y_prob = logreg.predict_proba(x_test_fold)[:, 1]

        log_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
        log_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
        Y_pred[n] = y_prediction
        Y_prob[n] =  y_prob

    print("\nLogisticRegression.....................................\n")
    self.possibility_acc_f1(log_accu_stratified,log_f1_stratified)

    self.dictAccuracy['LogisticRegression'] =  max(log_accu_stratified.values())*100
    self.dictF1['LogisticRegression'] = max(log_f1_stratified.values())*100
    targetNames = ['Yes', 'No']
    #print confusion matrix and AUC-ROC for maximum F1-score
    max_n = max(log_f1_stratified, key=lambda x:log_f1_stratified[x])
    self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
    print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))


#Decison Tree
def DT(self,plt):
    #Define dictionaries for possible folds
    dt_accu_stratified = {}
    dt_f1_stratified = {}
    Y_pred ={}
    Y_prob = {}
    feat_importance={}
    Y_test ={}
    #Define Model
    dtc = DecisionTreeClassifier()
    #Fold counter
    n = 0
    for train_index, test_index in self.skf.split(self.X ,self.Y):
        n=n+1
        x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
        y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
        Y_test[n] = y_test_fold
        dtc.fit(x_train_fold, y_train_fold)
        y_prediction = dtc.predict(x_test_fold)
        y_prob = dtc.predict_proba(x_test_fold)[:, 1]

        dt_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
        dt_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
        Y_pred[n] = y_prediction
        Y_prob[n] = y_prob

        feat_importance[n]= dtc.feature_importances_

    print("\nDecisionTree.....................................\n")
    self.possibility_acc_f1(dt_accu_stratified,dt_f1_stratified)
    self.dictAccuracy['DecisionTree'] =  max(dt_accu_stratified.values())*100
    self.dictF1['DecisionTree'] = max(dt_f1_stratified.values())*100
    targetNames = ['Yes', 'No']
    #print confusion matrix and AUC-ROC for maximum F1-score
    max_n = max(dt_f1_stratified, key=lambda x:dt_f1_stratified[x])
    self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
    print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))
    if plt:
        self.decisonFeature(self.dataset.columns.difference([target])
                            ,feat_importance[max_n])



#Random forest
def RF(self):
    #Define dictionaries for possible folds
    rf_accu_stratified = {}
    rf_f1_stratified = {}
    Y_pred ={}
    Y_test = {}
    Y_prob = {}

    #Define Model
    rf = RandomForestClassifier(n_estimators=500, random_state=42)
    #Fold counter
    n = 0
    for train_index, test_index in self.skf.split(self.X ,self.Y):
        n=n+1
        x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
        y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
        Y_test[n]=y_test_fold
        rf.fit(x_train_fold, y_train_fold)
        y_prediction = rf.predict(x_test_fold)
        y_prob = rf.predict_proba(x_test_fold)[:, 1]

        rf_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
        rf_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
        Y_pred[n] = y_prediction
        Y_prob[n] =  y_prob

    print("\nRandomForest.....................................\n")
    self.possibility_acc_f1(rf_accu_stratified,rf_f1_stratified)
    self.dictAccuracy['RandomForest'] =  max(rf_accu_stratified.values())*100
    self.dictF1['RandomForest'] = max(rf_f1_stratified.values())*100
    targetNames = ['Yes', 'No']
    #print confusion matrix and AUC-ROC for maximum F1-score
    max_n = max(rf_f1_stratified, key=lambda x:rf_f1_stratified[x])
    self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
    print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))

#KNN
def KNN(self):
    #Define dictionaries for possible folds
    knn_accu_stratified ={}
    knn_f1_stratified = {}
    Y_pred ={}
    Y_test={}
    Y_prob = {}

    #Define Model
    knn = KNeighborsClassifier()
    #Fold counter
    n = 0
    for train_index, test_index in self.skf.split(self.X ,self.Y):
        n=n+1
        x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
        y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
        Y_test[n]=y_test_fold
        knn.fit(x_train_fold, y_train_fold)
        y_prediction = knn.predict(x_test_fold)
        y_prob = knn.predict_proba(x_test_fold)[:, 1]

        knn_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
        knn_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
        Y_pred[n] = y_prediction
        Y_prob[n] =  y_prob


    print("\nKNN.....................................\n")
    self.possibility_acc_f1(knn_accu_stratified,knn_f1_stratified)
    self.dictAccuracy['KNN'] =  max(knn_accu_stratified.values())*100
    self.dictF1['KNN'] = max(knn_f1_stratified.values())*100
    targetNames = ['Yes', 'No']
    #print confusion matrix and AUC-ROC for maximum F1-score
    max_n = max(knn_f1_stratified, key=lambda x:knn_f1_stratified[x])
    self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
    print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))

#SVC
def SVC(self,kernel):
    #Define dictionaries for possible folds
    svc_accu_stratified = {}
    svc_f1_stratified = {}
    Y_pred ={}
    Y_test={}
    Y_prob = {}
    #Define Model
    clf = SVC(kernel=kernel, probability=True)
    #Fold counter
    n = 0
    for train_index, test_index in self.skf.split(self.X ,self.Y):
        n=n+1
        x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
        y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
        Y_test[n]=y_test_fold
        clf.fit(x_train_fold, y_train_fold)
        y_prediction = clf.predict(x_test_fold)
        y_prob = clf.predict_proba(x_test_fold)[:, 1]
        svc_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
        svc_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
        Y_pred[n] = y_prediction
        Y_prob[n] = y_prob

    print("\nSVC.....................................\n")
    self.possibility_acc_f1(svc_accu_stratified,svc_f1_stratified)
    self.dictAccuracy['SVC'] =  max(svc_accu_stratified.values())*100
    self.dictF1['SVC'] = max(svc_f1_stratified.values())*100
    targetNames = ['Yes', 'No']
    #print confusion matrix and AUC-ROC for maximum F1-score
    max_n = max(svc_f1_stratified, key=lambda x:svc_f1_stratified[x])
    self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
    print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))


#Metric Table
def table(self):
    self.dictF1 = sorted(self.dictF1.items(), key=lambda x:x[1],reverse=True)
    self.dictAccuracy = sorted(self.dictAccuracy.items(), key=lambda x:x[1] ,reverse=True)
    acc = pd.DataFrame.from_dict(self.dictAccuracy)
    f1 = pd.DataFrame.from_dict(self.dictF1)

    print("\nF1-Score.....................................\n")
    print(f1)

    print("\nAccuracy.....................................\n")
    print(acc)

#Feature importance
def decisonFeature(self ,features ,importances ):
    print("\nFeature Importance.....................................\n")
    wid = len(features)
    print(wid)
    figure(figsize=(wid,20))
    sorted_idx = importances.argsort()
    print(features[sorted_idx])
    plt.barh(features[sorted_idx], importances[sorted_idx])
    plt.show()


def ROC_AUC(self,Y_test,y_pred):
    fpr, tpr, thresh = roc_curve(Y_test, y_pred, pos_label=1)
    plt.figure(figsize=(8,5))
    plt.plot(fpr,tpr)
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
#Output
def testClassification(self):
    self.Logistic()
    self.DT(False)
    self.RF()
    self.KNN()
```

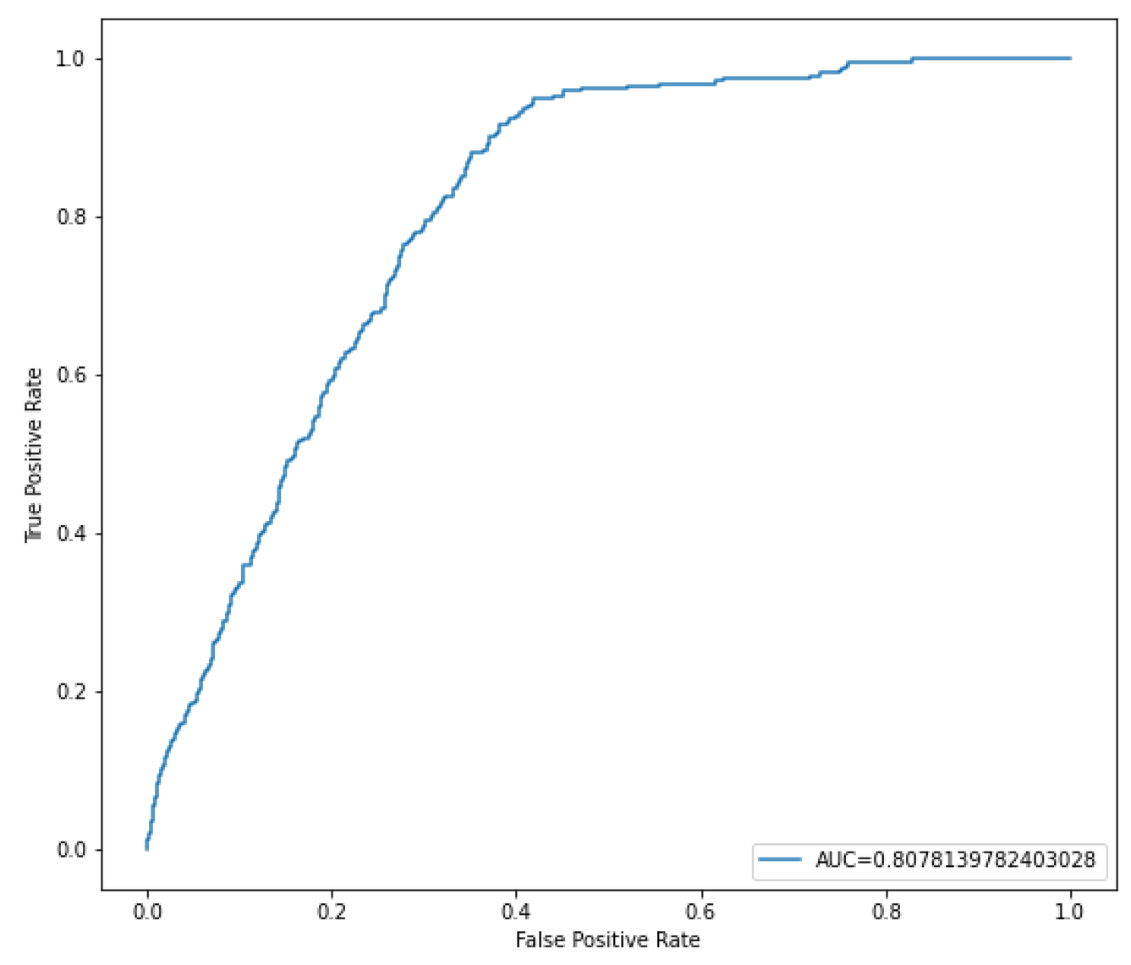
```python
        self.SVC('linear')
        self.table()
```

In [41]:
```python
model1 = Models_Startified(dataset,'FraudFound_P',3)
```

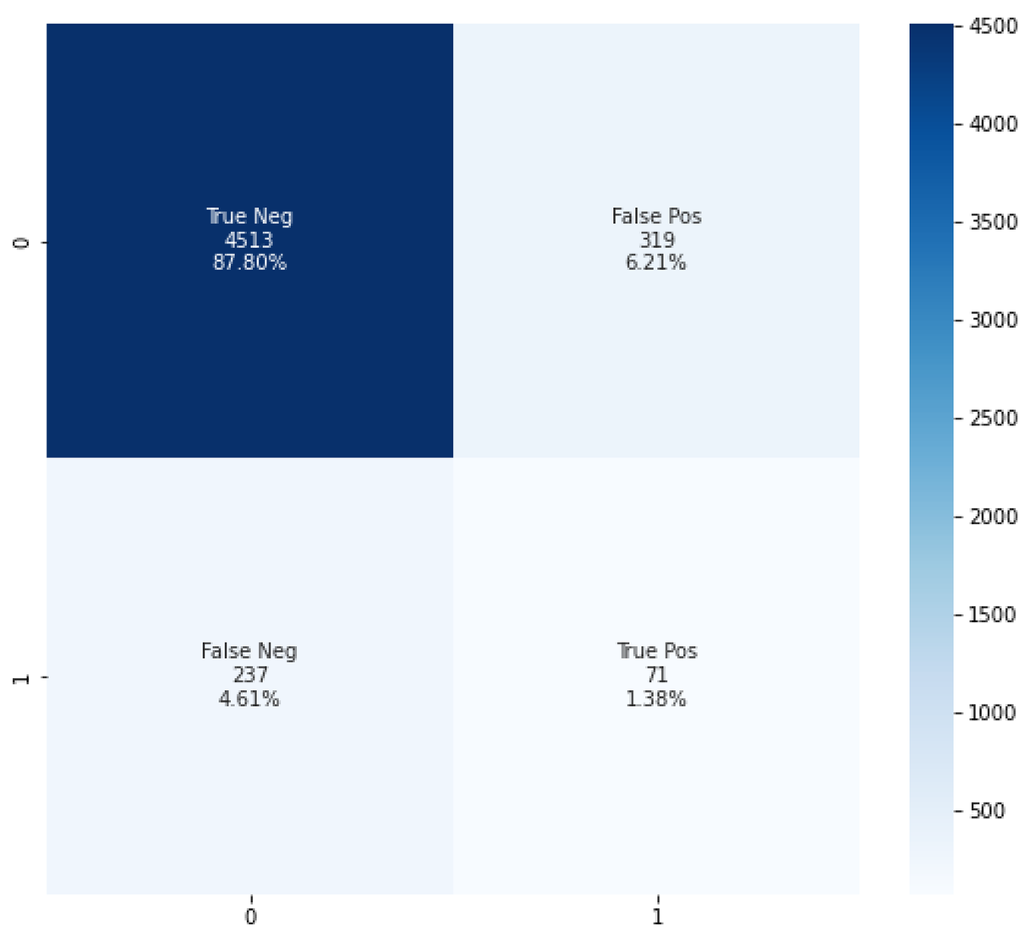
In [43]:
```python
model1.testClassification()
```

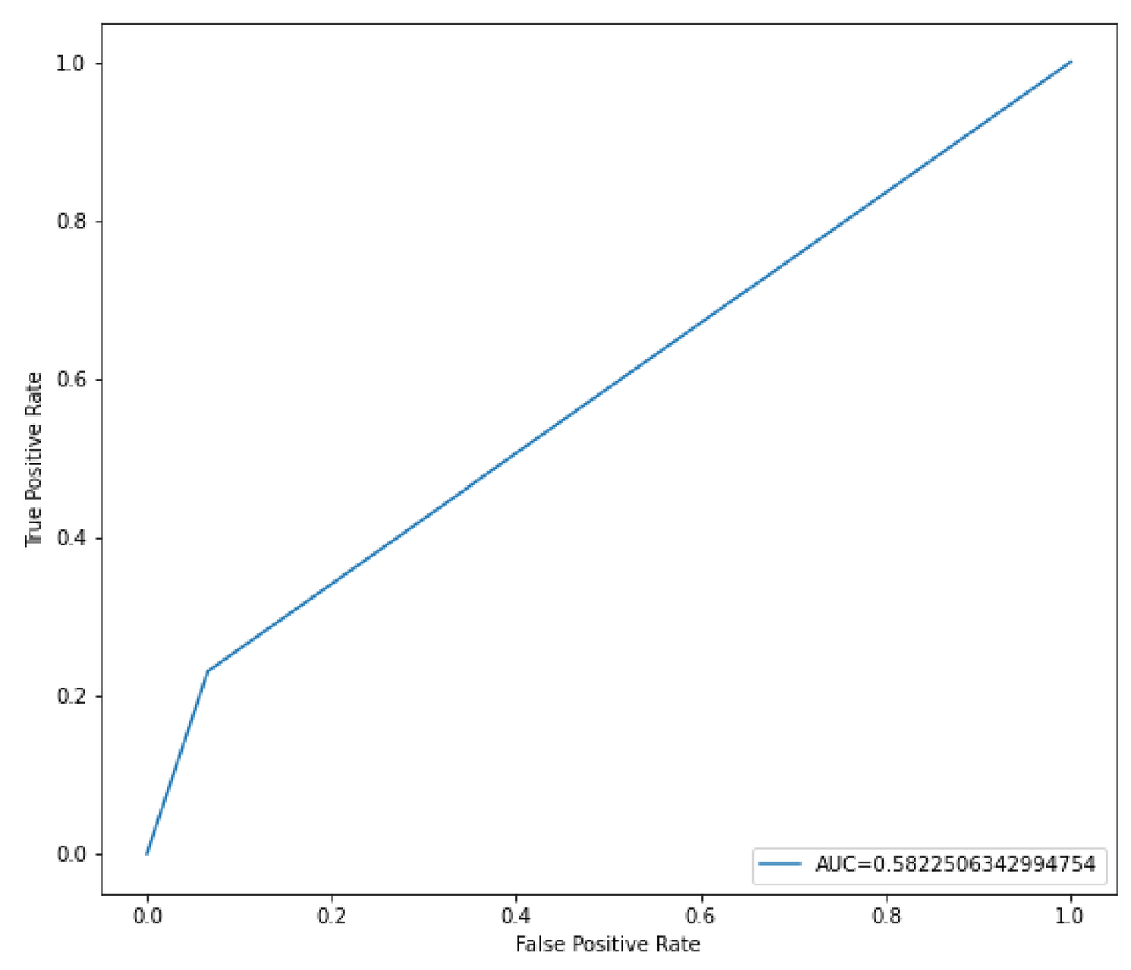
```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.................................

List of possible accuracy: dict_values([0.9400778210116731, 0.9400778210116731, 0.9400661607316598])

Maximum Accuracy That can be obtained from this model is: 94.00778210116731 %

Minimum Accuracy: 94.00661607316599 %

Overall Accuracy: 94.00739342516687 %

Standard Deviation is: 6.73206580451369e-06

List of possible F1-score: dict_values([0.0, 0.0, 0.0])

Maximum F1-score That can be obtained from this model is: 0.0 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.0 %

Standard Deviation is: 0.0
```



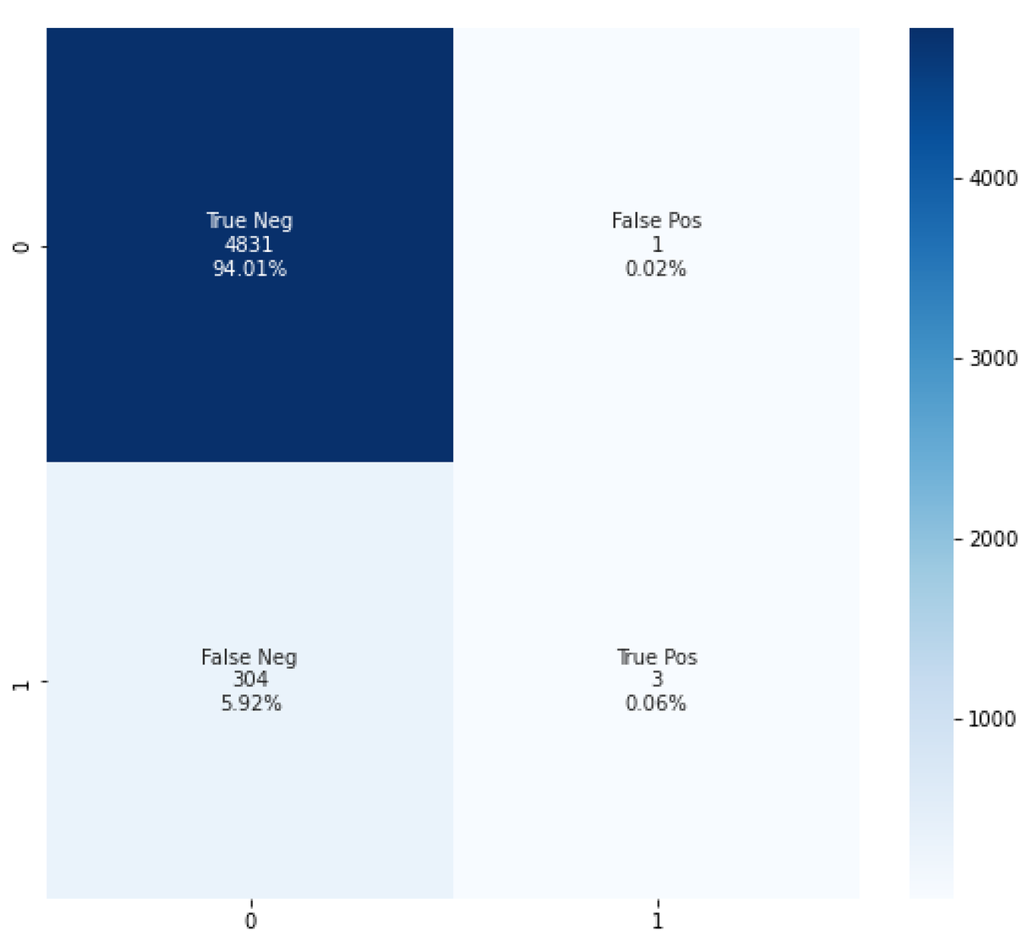


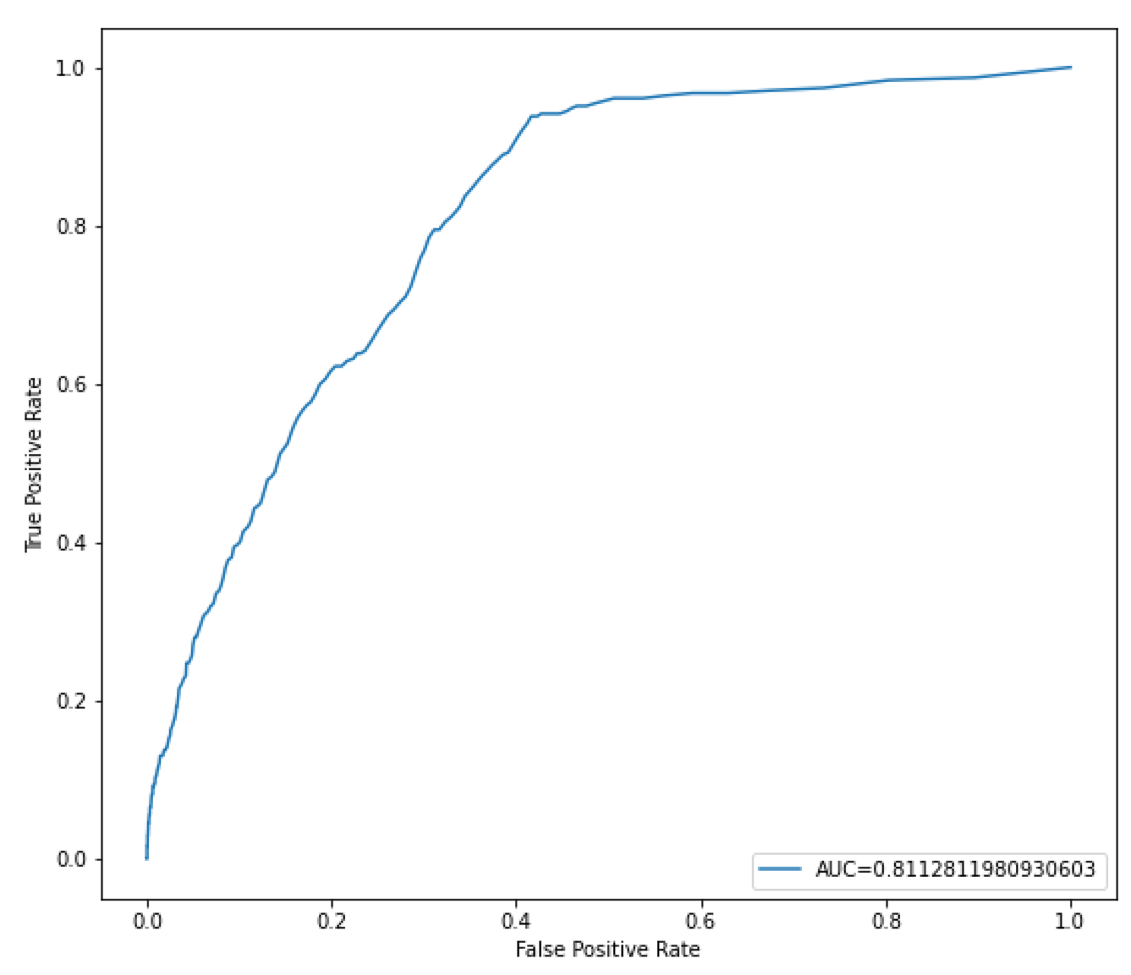

```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       1.00      0.00      0.00       308

    accuracy                           0.94      5140
   macro avg       0.97      0.50      0.48      5140
weighted avg       0.94      0.94      0.91      5140


DecisionTree.......................................

List of possible accuracy: dict_values([0.8918287937743191, 0.8959143968871596, 0.8955049620548745])

Maximum Accuracy That can be obtained from this model is: 89.59143968871595 %

Minimum Accuracy: 89.18287937743192 %

Overall Accuracy: 89.44160509054511 %

Standard Deviation is: 0.0022499630702340232

List of possible F1-score: dict_values([0.2034383954154728, 0.183206106870229, 0.1875945537065053])

Maximum F1-score That can be obtained from this model is: 20.34383954154728 %

Minimum F1-score: 18.3206106870229 %

Overall F1-score: 19.141301866406906 %

Standard Deviation is: 0.010642926332480524
```



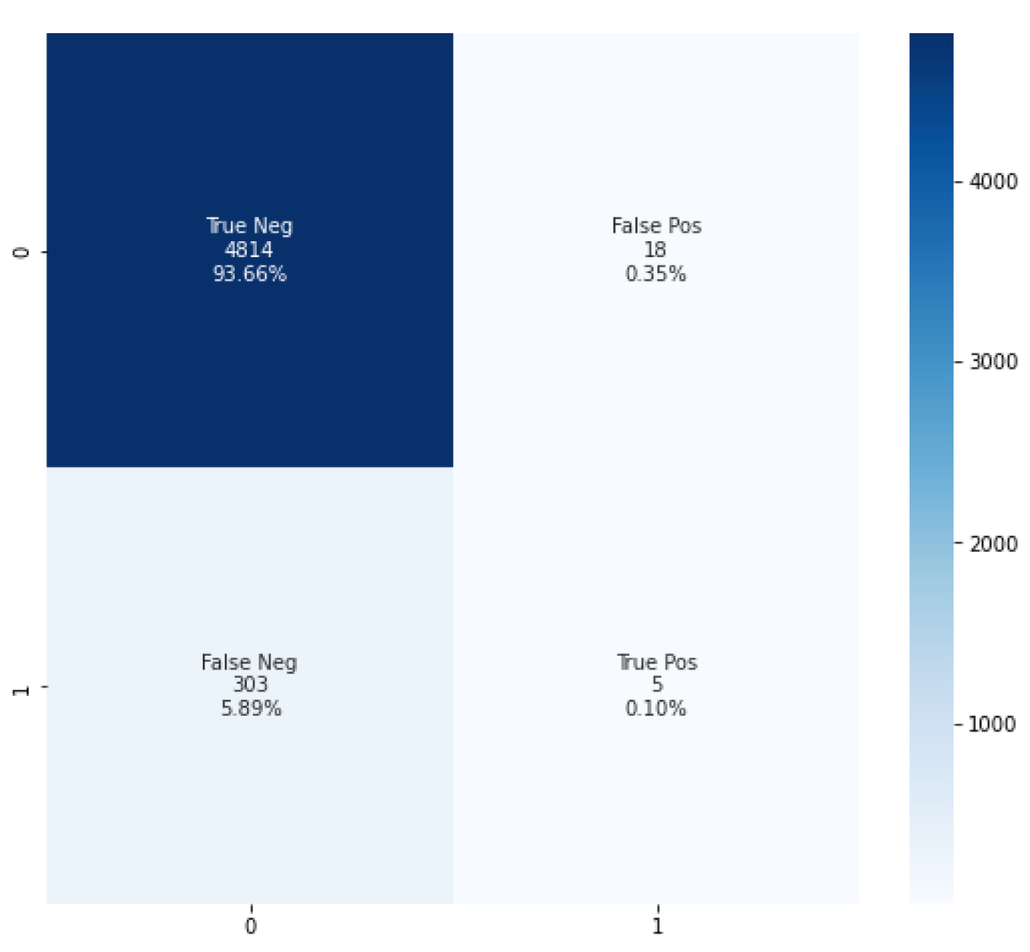


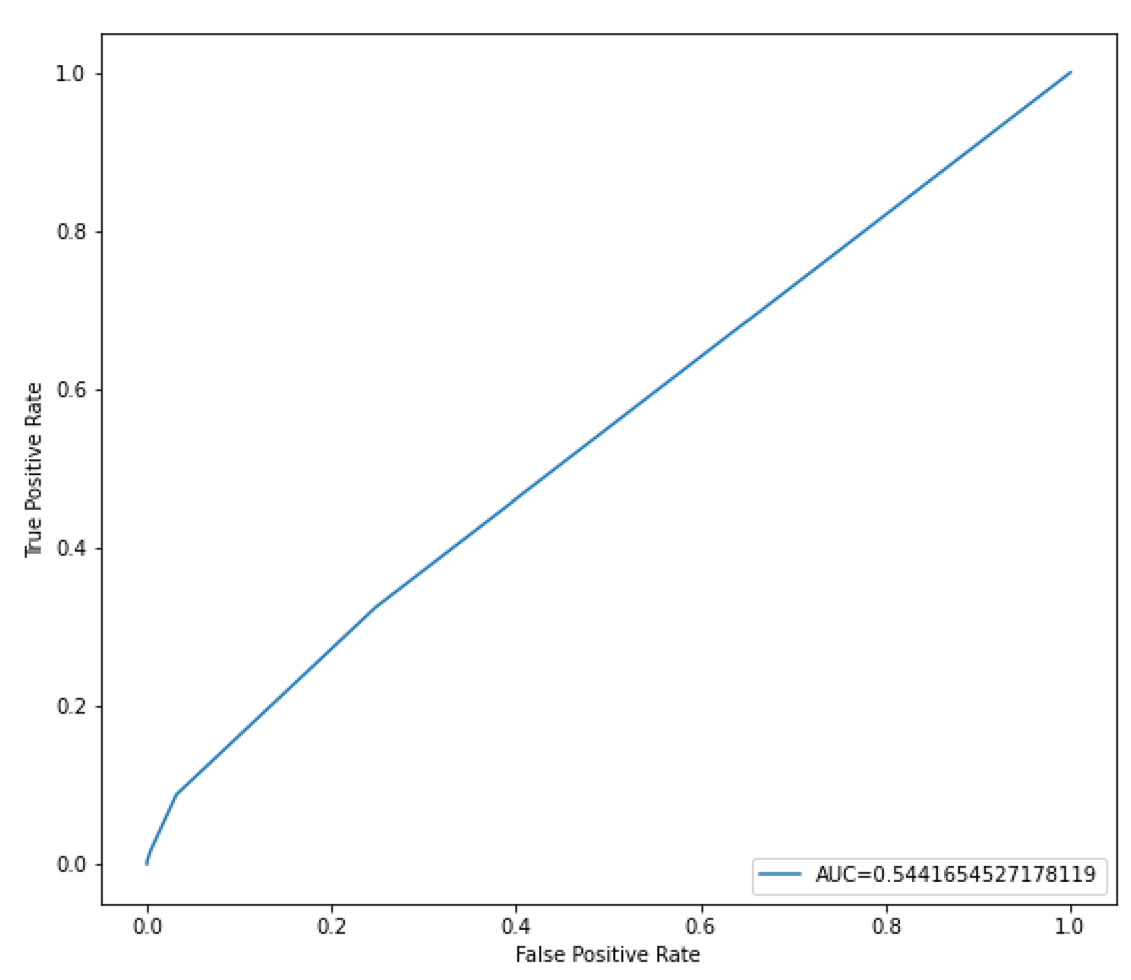

```
              precision    recall  f1-score   support

         Yes       0.95      0.93      0.94      4832
          No       0.18      0.23      0.20       308

    accuracy                           0.89      5140
   macro avg       0.57      0.58      0.57      5140
weighted avg       0.90      0.89      0.90      5140


RandomForest.......................................

List of possible accuracy: dict_values([0.9396887159533074, 0.9400778210116731, 0.9406499318933644])

Maximum Accuracy That can be obtained from this model is: 94.06499318933645 %

Minimum Accuracy: 93.96887159533074 %

Overall Accuracy: 94.01388229527817 %

Standard Deviation is: 0.0004835027905495407

List of possible F1-score: dict_values([0.0, 0.0064516129032258064, 0.019292604501607715])

Maximum F1-score That can be obtained from this model is: 1.9292604501607715 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.8581405801611174 %

Standard Deviation is: 0.009821056992827867
```





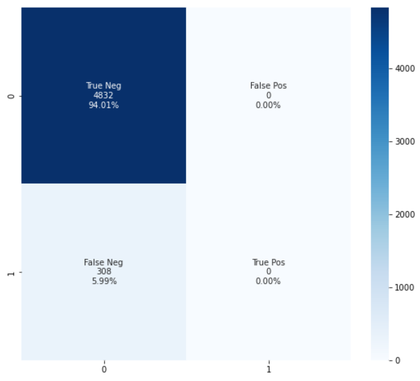

```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       0.75      0.01      0.02       307

    accuracy                           0.94      5139
   macro avg       0.85      0.50      0.49      5139
weighted avg       0.93      0.94      0.91      5139


KNN...............................................

List of possible accuracy: dict_values([0.9375486381322957, 0.9379377431906615, 0.9365635337614322])

Maximum Accuracy That can be obtained from this model is: 93.79377431906615 %

Minimum Accuracy: 93.65635337614322 %

Overall Accuracy: 93.73499716947966 %

Standard Deviation is: 0.0007083178339468438

List of possible F1-score: dict_values([0.030211480362537763, 0.01846153846153846, 0.012121212121212121])

Maximum F1-score That can be obtained from this model is: 3.021148036253776 %

Minimum F1-score: 1.2121212121212122 %

Overall F1-score: 2.0264743648429446 %

Standard Deviation is: 0.009178949448074201
```

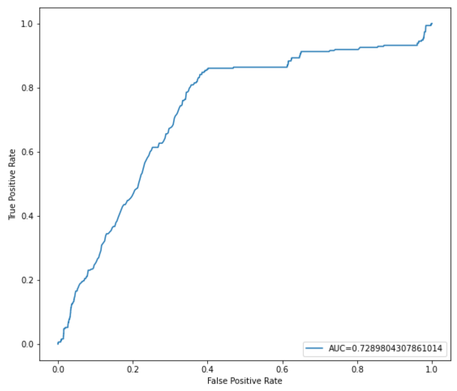





```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
```

```
          No       0.22      0.02      0.03       308

    accuracy                           0.94      5140
   macro avg       0.58      0.51      0.50      5140
weighted avg       0.90      0.94      0.91      5140


SVC.............................................

List of possible accuracy: dict_values([0.9400778210116731, 0.9400778210116731, 0.9402607511188947])

Maximum Accuracy That can be obtained from this model is: 94.02607511188947 %

Minimum Accuracy: 94.00778210116731 %

Overall Accuracy: 94.01387977140804 %

Standard Deviation is: 0.00010561474664727239

List of possible F1-score: dict_values([0.0, 0.0, 0.0])

Maximum F1-score That can be obtained from this model is: 0.0 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.0 %

Standard Deviation is: 0.0
```






```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       1.00      0.00      0.00       308

    accuracy                           0.94      5140
   macro avg       0.97      0.50      0.48      5140
weighted avg       0.94      0.94      0.91      5140


F1-Score.........................................

                    0         1
0        DecisionTree  20.343840
1                 KNN   3.021148
2        RandomForest   1.929260
3  LogisticRegression   0.000000
4                 SVC   0.000000

Accuracy.........................................

                    0         1
0        RandomForest  94.064993
1                 SVC  94.026075
2  LogisticRegression  94.007782
3                 KNN  93.793774
4        DecisionTree  89.591440
```

Explore dataset

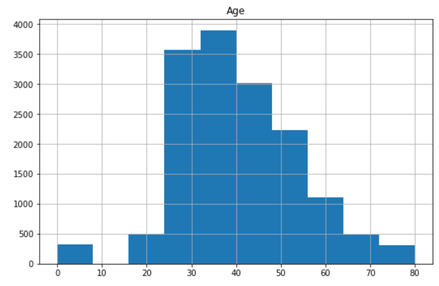
In [41]:
```
#copy
dataset_EDA = dataset.copy()
```

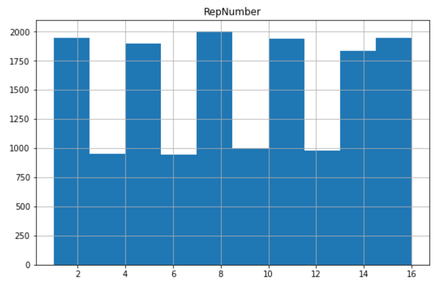
1.Numerical

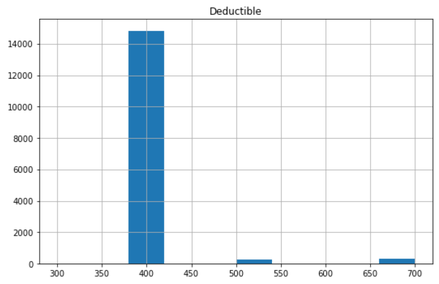
In [42]:
```
numericalOrginal = [ 'Age'
    ,'RepNumber'
    ,'Deductible'
     ,'DriverRating'
       ,'Year']
```

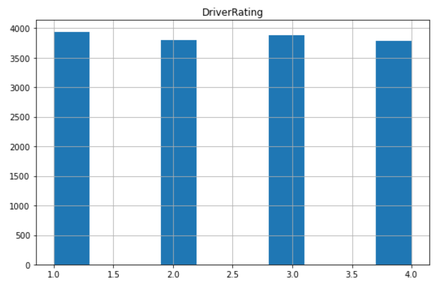
In [43]:
```
dataset[numericalOrginal].hist(figsize=(20,20))
```

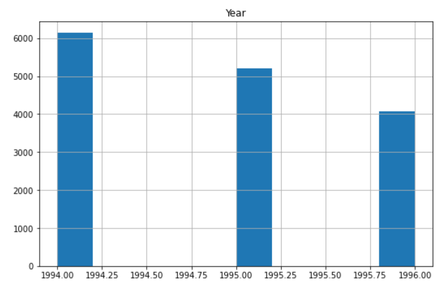
Out[43]:
```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'RepNumber'}>],
       [<AxesSubplot:title={'center':'Deductible'}>,
        <AxesSubplot:title={'center':'DriverRating'}>],
       [<AxesSubplot:title={'center':'Year'}>, <AxesSubplot:>]],
      dtype=object)
```











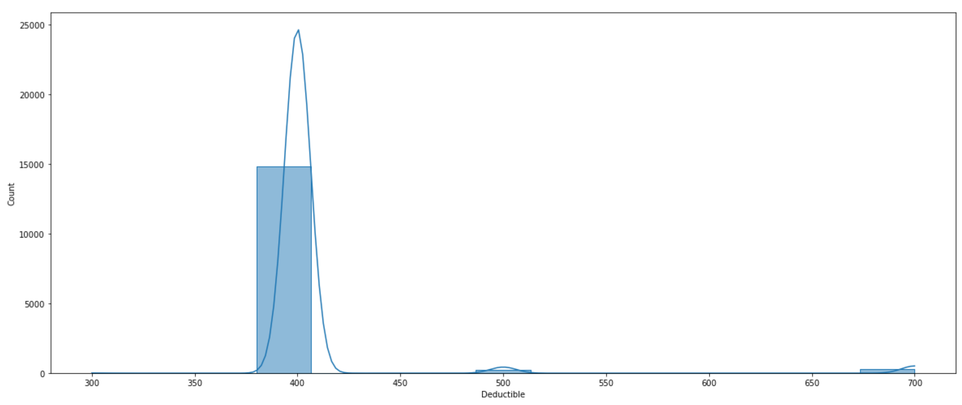
A. Scaling

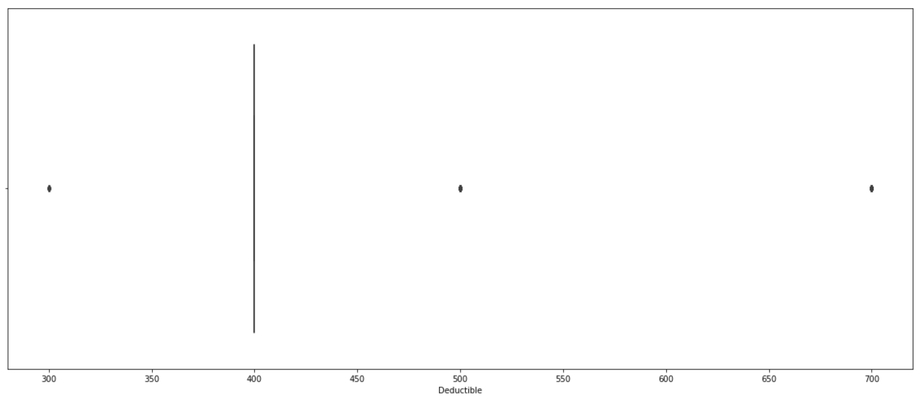
Deductible

In [44]:
```
featureAnalysis('Deductible',dataset)
```

Out[44]:

	count	mean	std	min	25%	50%	75%	max
Deductible	15419.0	407.70478	43.952379	300.0	400.0	400.0	400.0	700.0





In [45]:
```
dataset['Deductible'].unique()
```

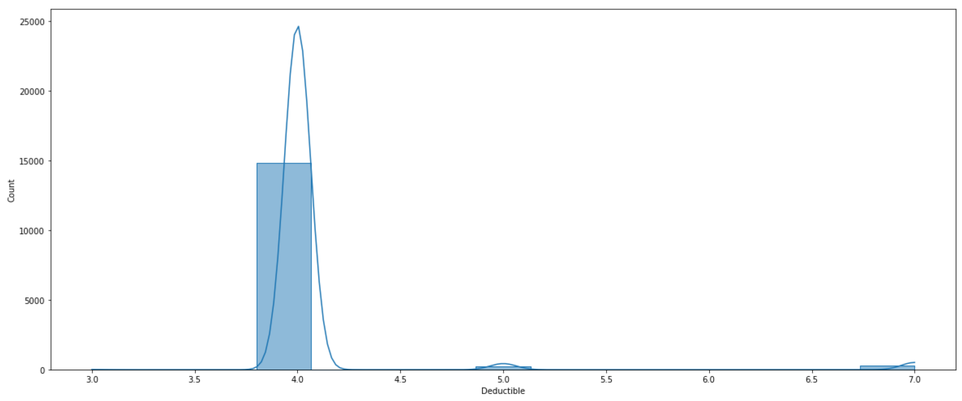
Out[45]:
```
array([300, 400, 500, 700], dtype=int64)
```

In [46]:
```
dataset['Deductible'] = dataset['Deductible'] / 100
```

In [47]:
```
featureAnalysis('Deductible',dataset)
```

Out[47]:

	count	mean	std	min	25%	50%	75%	max
Deductible	15419.0	4.077048	0.439524	3.0	4.0	4.0	4.0	7.0

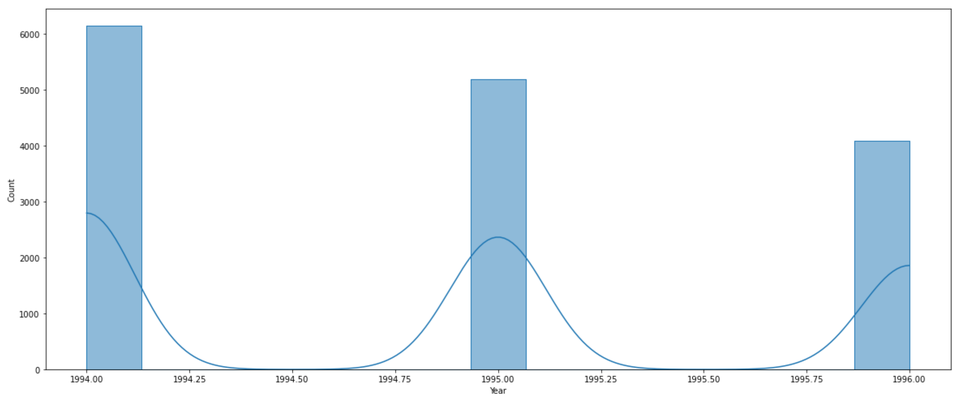


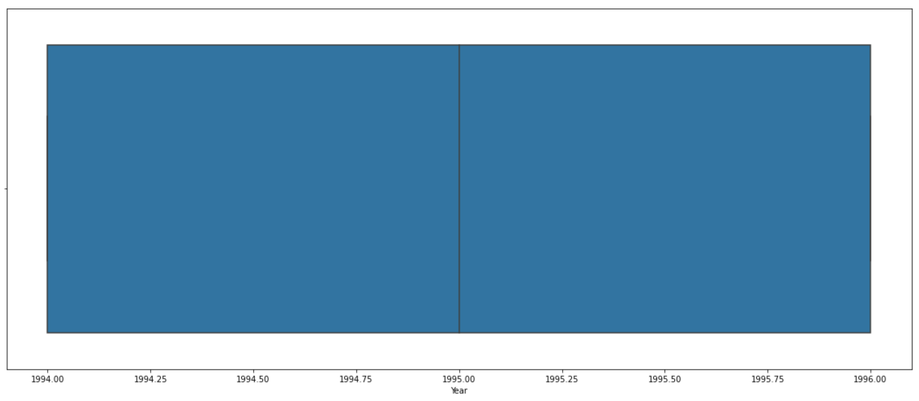
Year

In [48]:
```
featureAnalysis('Year',dataset)
```

Out[48]:

	count	mean	std	min	25%	50%	75%	max
Year	15419.0	1994.866528	0.803309	1994.0	1994.0	1995.0	1996.0	1996.0





In [49]:
```
dataset['Year'].unique()
```

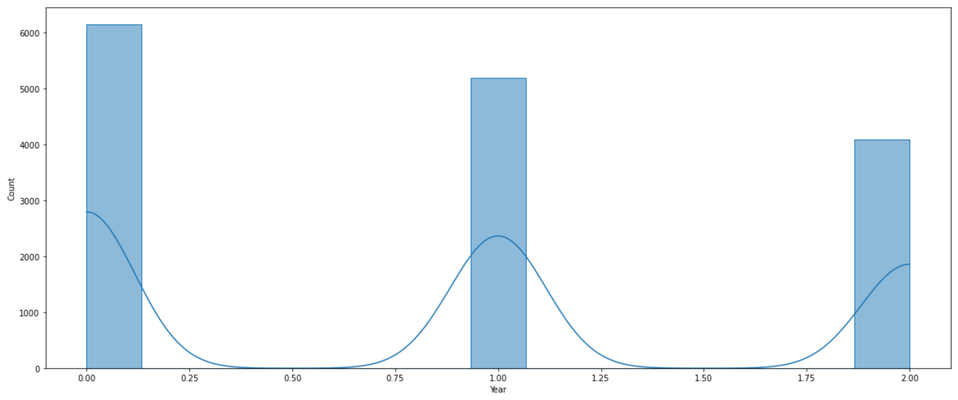
Out[49]:
```
array([1994, 1995, 1996], dtype=int64)
```

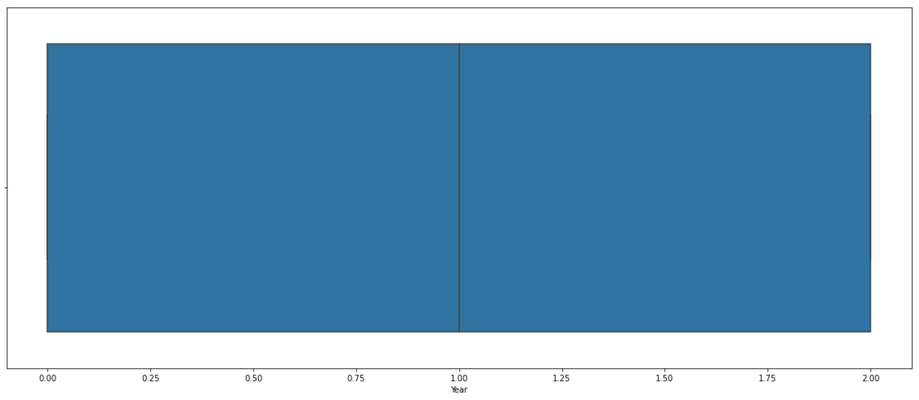
In [50]:
```
map_years = {1994:0, 1995:1 ,1996:2}
dataset['Year']=dataset.Year.map(map_years)
```

In [51]:
```
featureAnalysis('Year',dataset)
```

Out[51]:

	count	mean	std	min	25%	50%	75%	max
Year	15419.0	0.866528	0.803309	0.0	0.0	1.0	2.0	2.0



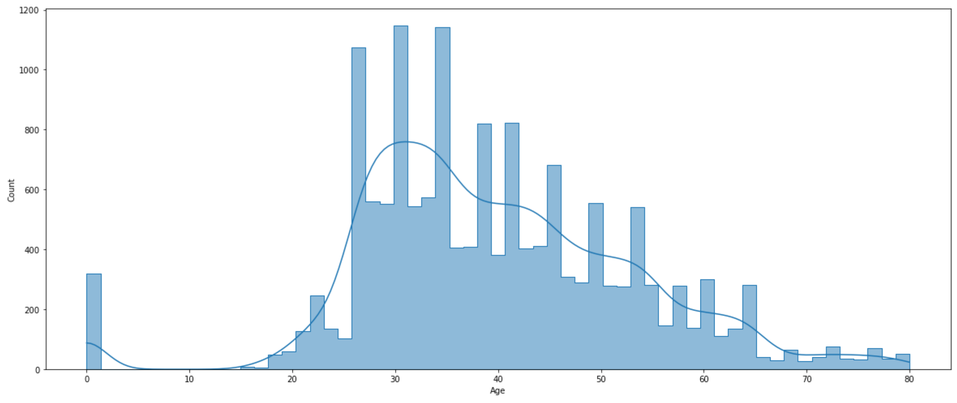


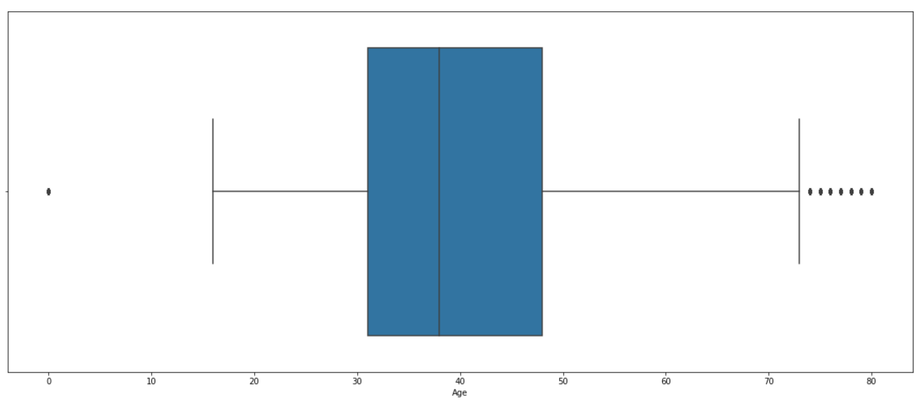
Age

In [52]:
```
featureAnalysis('Age',dataset)
```

Out[52]:

	count	mean	std	min	25%	50%	75%	max
Age	15419.0	39.858292	13.488996	0.0	31.0	38.0	48.0	80.0





In [53]:
```
len(dataset[dataset['Age'] == 0])
```

Out[53]: 319

In [54]:
```
#detect null values
```

319 people ages is zero and logically its not possible so they are null values

In [55]:
```
319/ dataset.shape[0]
```

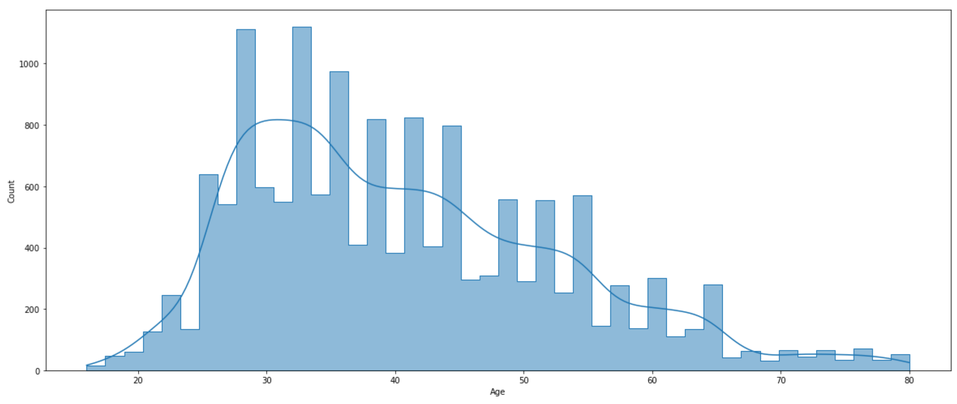
Out[55]: 0.02068876062001427

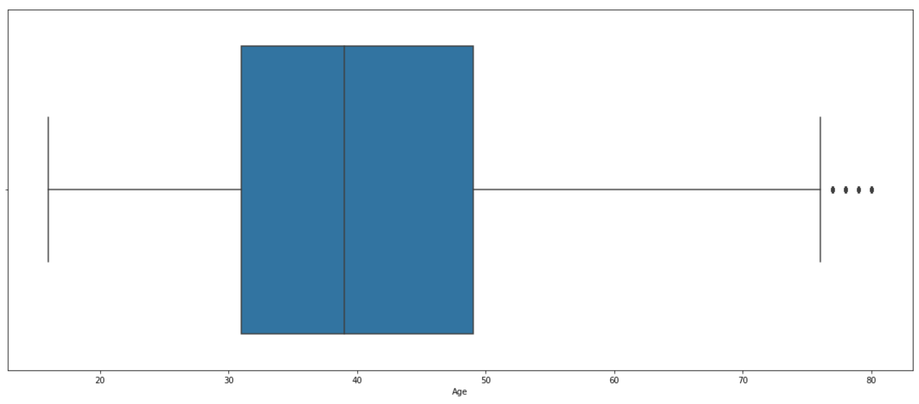
0.02 of the whole dataset so Im going to fill them with mean or median

In [56]:
```
featureAnalysis('Age',dataset[dataset['Age'] != 0])
```

Out[56]:

	count	mean	std	min	25%	50%	75%	max
Age	15100.0	40.700331	12.309493	16.0	31.0	39.0	49.0	80.0





In [57]:
```
dataset['Age'].replace(to_replace = 0, value = 40, inplace=True)
```

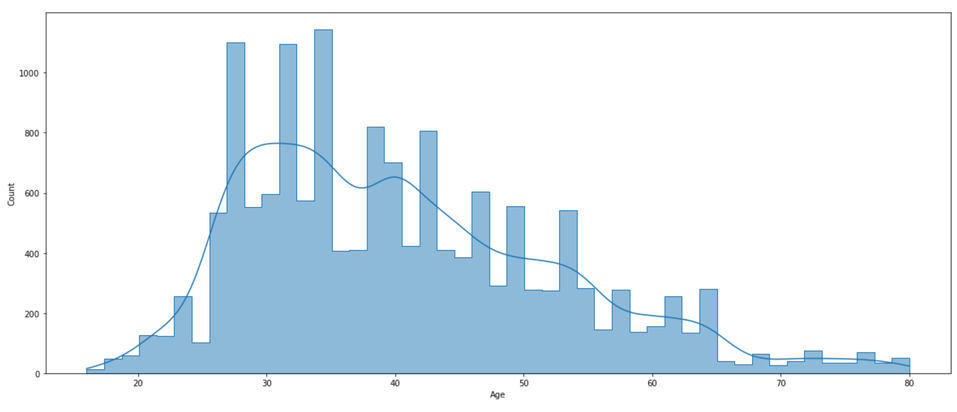
In [58]:
```
len(dataset[dataset['Age'] == 0])
```

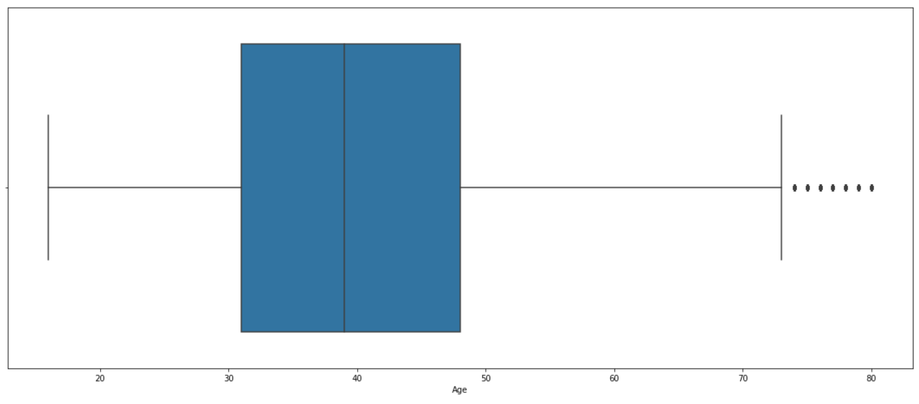
Out[58]: 0

In [59]:
```
featureAnalysis('Age',dataset)
```

Out[59]:

	count	mean	std	min	25%	50%	75%	max
Age	15419.0	40.685842	12.181893	16.0	31.0	39.0	48.0	80.0

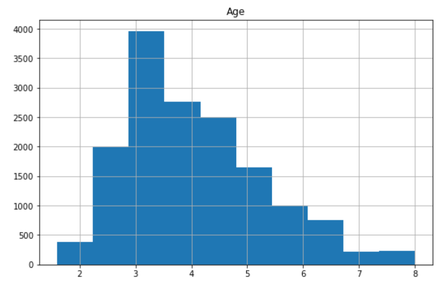


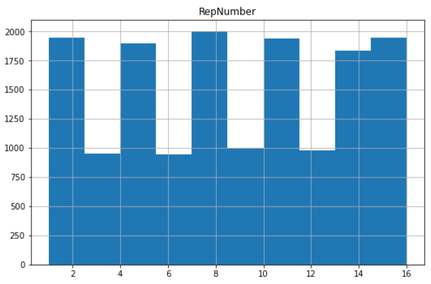


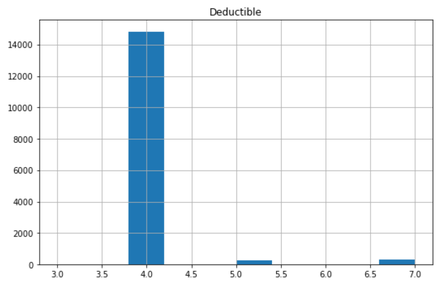
In [60]:
```
dataset['Age'] = dataset['Age'] / 10
```

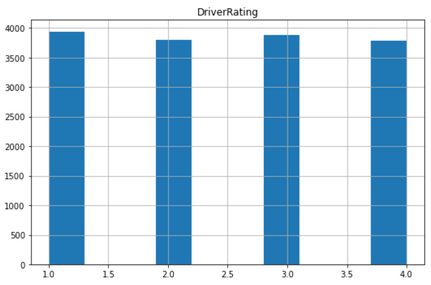
In [61]:
```
dataset[numericalOrginal].hist(figsize=(20,20))
```

Out[61]:
```
array([[<AxesSubplot:title={'center':'Age'}>,
        <AxesSubplot:title={'center':'RepNumber'}>],
       [<AxesSubplot:title={'center':'Deductible'}>,
        <AxesSubplot:title={'center':'DriverRating'}>],
       [<AxesSubplot:title={'center':'Year'}>, <AxesSubplot:>]],
      dtype=object)
```









In [62]:
```
dataset[numericalOrginal].describe()
```

Out[62]:

	Age	RepNumber	Deductible	DriverRating	Year
count	15419.000000	15419.000000	15419.000000	15419.000000	15419.000000
mean	4.068584	8.482846	4.077048	2.487840	0.866528
std	1.218189	4.599798	0.439524	1.119482	0.803309
min	1.600000	1.000000	3.000000	1.000000	0.000000
25%	3.100000	5.000000	4.000000	1.000000	0.000000
50%	3.900000	8.000000	4.000000	2.000000	1.000000
75%	4.800000	12.000000	4.000000	3.000000	2.000000
max	8.000000	16.000000	7.000000	4.000000	2.000000

B. Adding new features

In [63]:
```
numericalAdd = numericalOrginal.copy()
```

In [64]:
```
numericalAdd
```

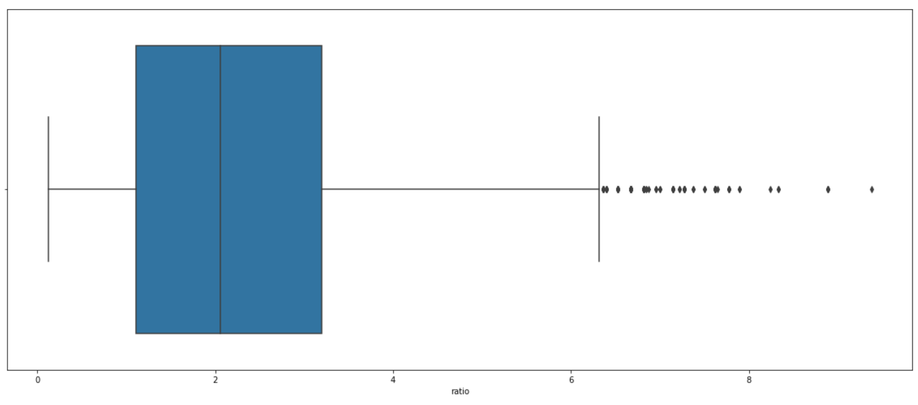
Out[64]:
```
['Age', 'RepNumber', 'Deductible', 'DriverRating', 'Year']
```

In [65]:
```
#A ratio of age and number of accidents
dataset['ratio'] = dataset['RepNumber'] / dataset['Age']
```

In [66]:
```
featureAnalysis('ratio',dataset)
```

Out[66]:

	count	mean	std	min	25%	50%	75%	max
ratio	15419.0	2.273016	1.447594	0.125	1.111111	2.058824	3.2	9.375



In [67]:
```
numericalAdd.append('ratio')
```

In [68]:
```
dataset['DriverRating'].unique()
```

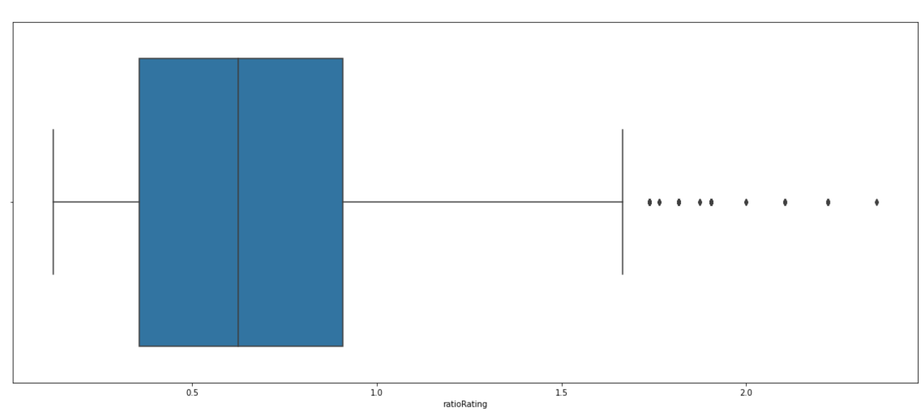
Out[68]:
```
array([1, 4, 3, 2], dtype=int64)
```

In [69]:
```
# A ratio of DriverRating and the Age of client
dataset['ratioRating'] = dataset['DriverRating'] / dataset['Age']
```

In [70]:
```
featureAnalysis('ratioRating',dataset)
```

Out[70]:

	count	mean	std	min	25%	50%	75%	max
ratioRating	15419.0	0.665933	0.367062	0.125	0.357143	0.625	0.909091	2.352941



In [71]:
```
numericalAdd.append('ratioRating')
```

In [72]:
```
numericalAdd
```

Out[72]:
```
['Age',
 'RepNumber',
```

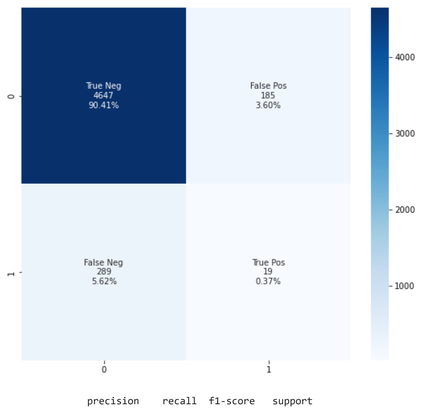
```
'Deductible',
'DriverRating',
'Year',
'ratio',
'ratioRating']
```

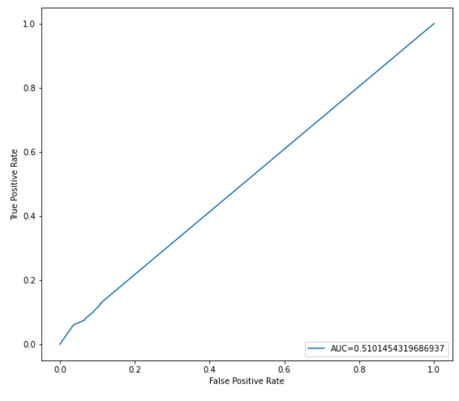
In [73]:
```
XNum = dataset[numericalAdd]
Y = dataset[target]
numericalData = pd.concat([XNum, Y], axis=1)
```

In [74]:
```
modelAddNumerical = Models_Startified(numericalData,'FraudFound_P',3)
```

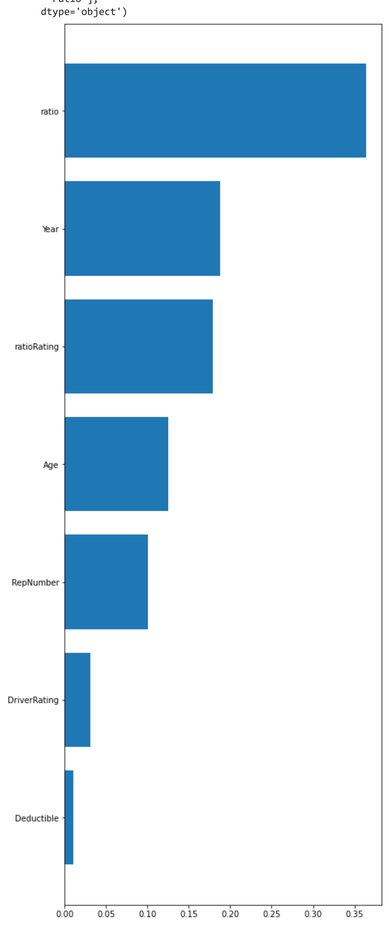
In [75]:
```
modelAddNumerical.DT(True)
```

```
DecisionTree.....................................

List of possible accuracy: dict_values([0.9077821011673152, 0.9153696498054474, 0.9112667834208991])

Maximum Accuracy That can be obtained from this model is: 91.53696498054474 %

Minimum Accuracy: 90.77821011673151 %

Overall Accuracy: 91.14728447978872 %

Standard Deviation is: 0.0037979693135251155

List of possible F1-score: dict_values([0.07421875, 0.05228758169934641, 0.04602510460251046])

Maximum F1-score That can be obtained from this model is: 7.421875 %

Minimum F1-score: 4.602510460251046 %

Overall F1-score: 5.751047876728562 %

Standard Deviation is: 0.014804708728528291
```





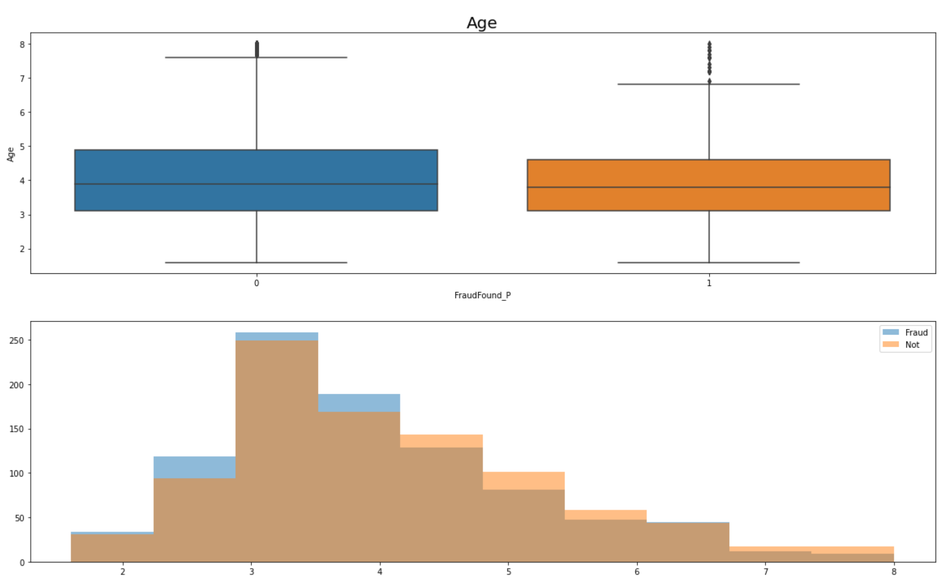

```
              precision    recall  f1-score   support

         Yes       0.94      0.96      0.95      4832
          No       0.09      0.06      0.07       308

    accuracy                           0.91      5140
   macro avg       0.52      0.51      0.51      5140
weighted avg       0.89      0.91      0.90      5140


Feature Importance.................................

7
Index(['Deductible', 'DriverRating', 'RepNumber', 'Age', 'ratioRating', 'Year',
       'ratio'],
      dtype='object')
```

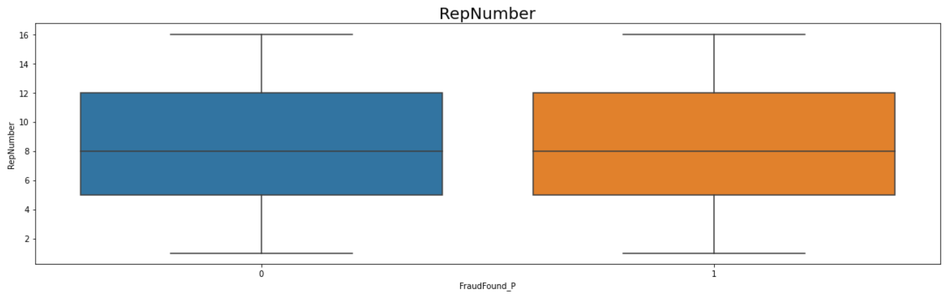


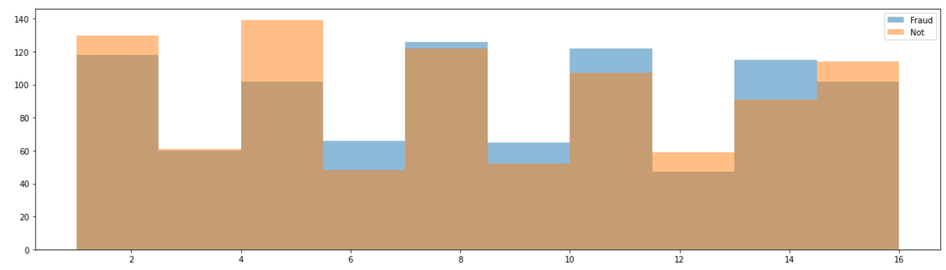
Let's check frauds

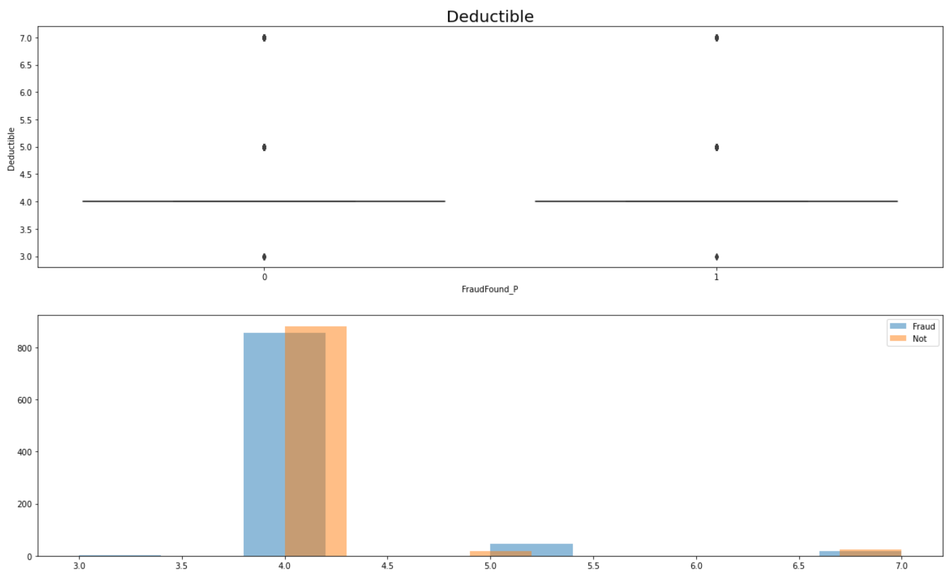
In [76]:
```
def compare(feature,dataset):
    num_1 = len(dataset[dataset[target]==1])
    num_0 = len(dataset[dataset[target]==0])
    undersampled_dataset = pd.concat([dataset[dataset[target]==0].sample(num_1) ,dataset[dataset[target]==1] ])

    fraud = undersampled_dataset[undersampled_dataset['FraudFound_P'] == 1]
    NotFraud = undersampled_dataset[undersampled_dataset['FraudFound_P'] == 0]

    print("\n")
    print("\n")
    fig, ax = plt.subplots(2, 1, figsize=(20, 12))
    pyplot.hist(fraud[feature], alpha=0.5, label='Fraud')
    pyplot.hist(NotFraud[feature], alpha=0.5, label='Not')
    pyplot.legend(loc='upper right')
    sns.boxplot(x=target, y=feature, data=dataset,ax=ax[0]).set_title(str(feature),fontsize = 20)
    pyplot.show()
    print("\n")
    print("\n")
```

In [77]:
```
for feature in numericalAdd:
    compare(feature,dataset)
```

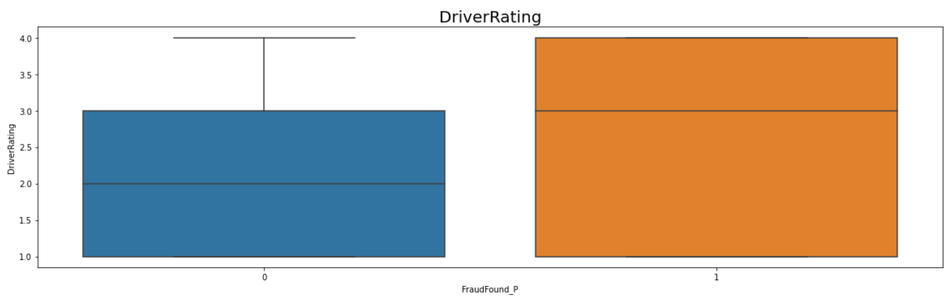


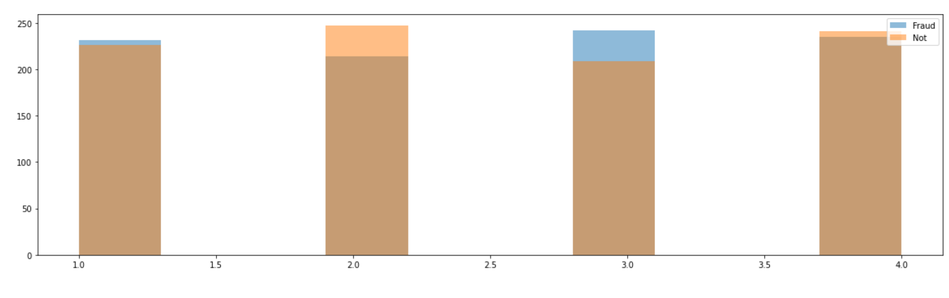

RepNumber
RepNumber
FraudFound_P

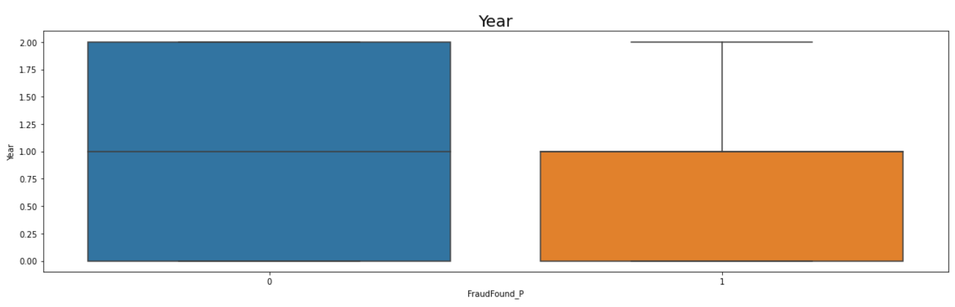

Fraud
Not

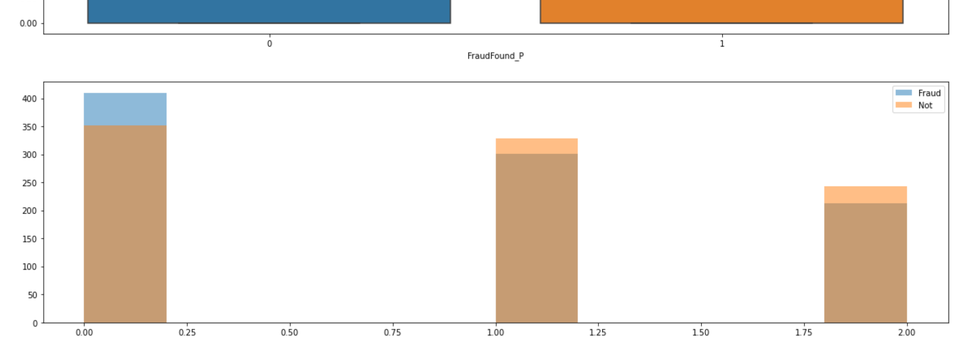

Deductible
Deductible
FraudFound_P

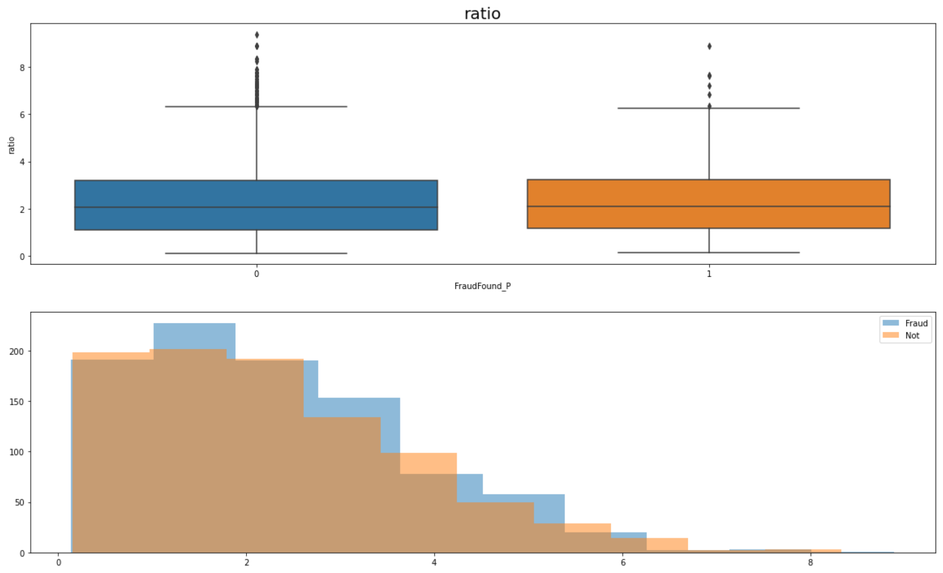
Fraud
Not


DriverRating
DriverRating
FraudFound_P

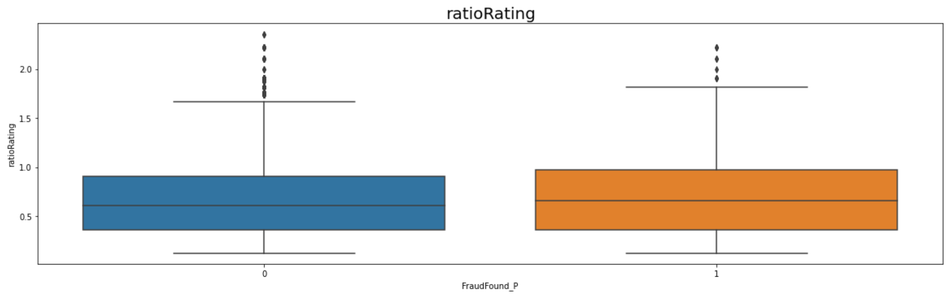

Fraud
Not

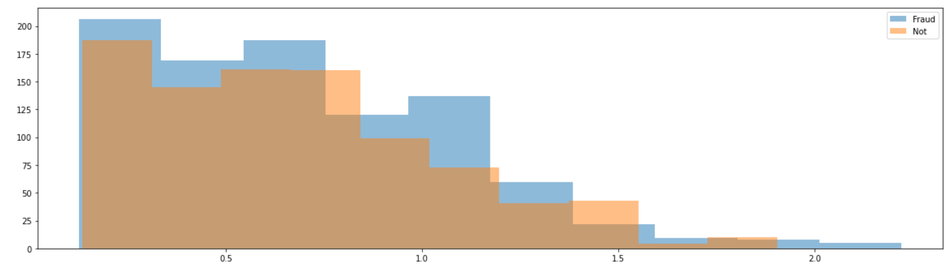

Year
Year
FraudFound_P


Fraud
Not


ratio
ratio
FraudFound_P

Fraud
Not





In [78]:
```
numericalData.describe()
```

Out[78]:

	Age	RepNumber	Deductible	DriverRating	Year	ratio	ratioRating	FraudFound_P
count	15419.000000	15419.000000	15419.000000	15419.000000	15419.000000	15419.000000	15419.000000	15419.000000
mean	4.068584	8.482846	4.077048	2.487840	0.866528	2.273016	0.665933	0.059861
std	1.218189	4.599798	0.439524	1.119482	0.803309	1.447594	0.367062	0.237237
min	1.600000	1.000000	3.000000	1.000000	0.000000	0.125000	0.125000	0.000000
25%	3.100000	5.000000	4.000000	1.000000	0.000000	1.111111	0.357143	0.000000
50%	3.900000	8.000000	4.000000	2.000000	1.000000	2.058824	0.625000	0.000000
75%	4.800000	12.000000	4.000000	3.000000	2.000000	3.200000	0.909091	0.000000
max	8.000000	16.000000	7.000000	4.000000	2.000000	9.375000	2.352941	1.000000

2.Ordinals

In [79]:
```
dataset_ordinal = dataset.copy()
```

In [80]:
```
ordinal
```

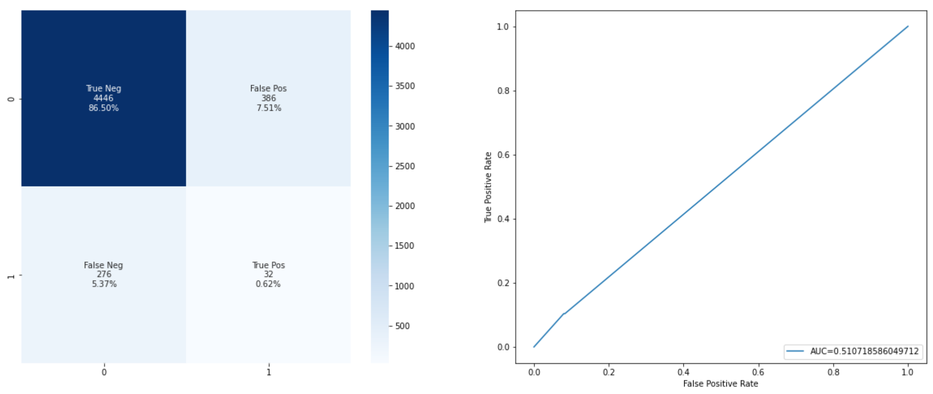
Out[80]:
```
['Month',
 'DayOfWeek',
 'DayOfWeekClaimed',
 'MonthClaimed',
 'VehiclePrice',
 'Days_Policy_Accident',
 'Days_Policy_Claim',
 'PastNumberOfClaims',
 'AgeOfVehicle',
 'AgeOfPolicyHolder',
 'NumberOfSuppliments',
 'AddressChange_Claim',
 'NumberOfCars']
```

Adding Feature

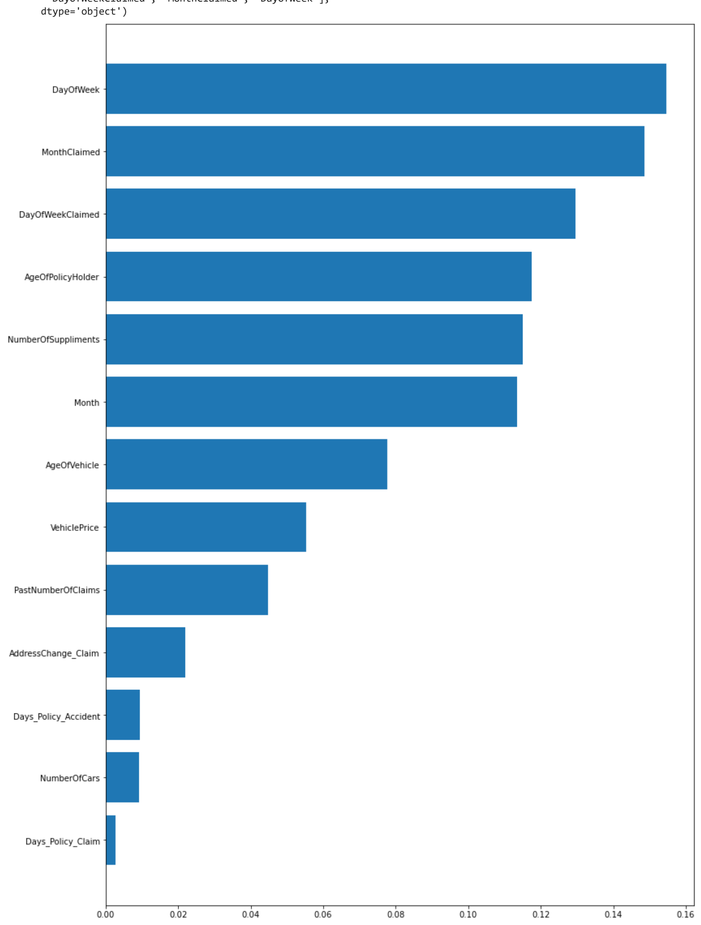
In [81]:
```
XOrdinal= dataset[ordinal]
Y = dataset[target]
ordinalData = pd.concat([XOrdinal, Y], axis=1)
```

In [82]:
```
modelordinalData= Models_Startified(ordinalData,'FraudFound_P',3)
modelordinalData.DT(True)
```

```
DecisionTree.....................................

List of possible accuracy: dict_values([0.8803501945525292, 0.8712062256809339, 0.8700136213271065])

Maximum Accuracy That can be obtained from this model is: 88.03501945525292 %

Minimum Accuracy: 87.00136213271065 %

Overall Accuracy: 87.38566805201899 %

Standard Deviation is: 0.0056550746814107 48

List of possible F1-score: dict_values([0.08345752608047691, 0.0881542699724518, 0.08493150684931508])

Maximum F1-score That can be obtained from this model is: 8.81542699724518 %

Minimum F1-score: 8.345752608047691 %

Overall F1-score: 8.551443430074793 %

Standard Deviation is: 0.0024020208381540626
```




```
              precision    recall  f1-score   support

         Yes       0.94      0.92      0.93      4832
          No       0.08      0.10      0.09       308

    accuracy                           0.87      5140
   macro avg       0.51      0.51      0.51      5140
weighted avg       0.89      0.87      0.88      5140


Feature Importance.................................

13
Index(['Days_Policy_Claim', 'NumberOfCars', 'Days_Policy_Accident',
       'AddressChange_Claim', 'PastNumberOfClaims', 'VehiclePrice',
       'AgeOfVehicle', 'Month', 'NumberOfSuppliments', 'AgeOfPolicyHolder',
       'DayOfWeekClaimed', 'MonthClaimed', 'DayOfWeek'],
      dtype='object')
```



In [83]:
```
ordinalAdd = ordinal
```

1.RatioRepNumber

In [84]:
```
dataset['AgeOfPolicyHolder'].unique()
```

Out[84]:
```
array([ 5,  6, 10, 15,  4,  7,  1, 20,  2], dtype=int64)
```

In [85]:
```
dataset['RepNumber'].unique()
```

Out[85]:
```
array([12, 15,  7,  4,  3, 14,  1, 13, 11, 16,  6,  2,  8,  5,  9, 10],
      dtype=int64)
```

In [86]:
```
dataset['ratioRepNumber'] = dataset['RepNumber'] / dataset['AgeOfPolicyHolder']
```

In [87]:
```
ordinalAdd.append('ratioRepNumber')
```

2.VehiclePrice per Brand

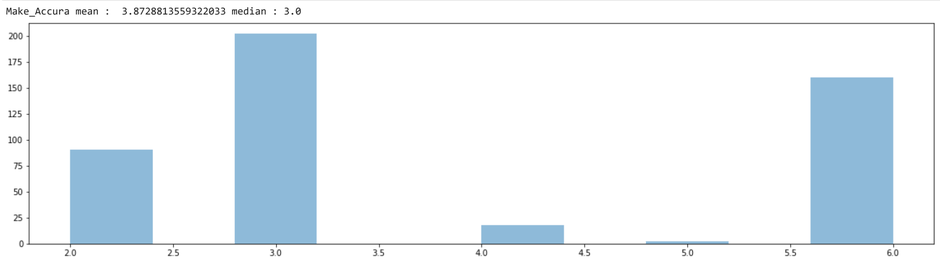
In [88]:
```
make = ['Make_Accura', 'Make_BMW', 'Make_Chevrolet', 'Make_Dodge',
       'Make_Ferrari', 'Make_Ford', 'Make_Honda', 'Make_Jaguar', 'Make_Lexus',
       'Make_Mazda', 'Make_Mecedes', 'Make_Mercury', 'Make_Nisson',
```

```
        'Make_Pontiac', 'Make_Porche', 'Make_Saab', 'Make_Saturn',
        'Make_Toyota', 'Make_VW']
```

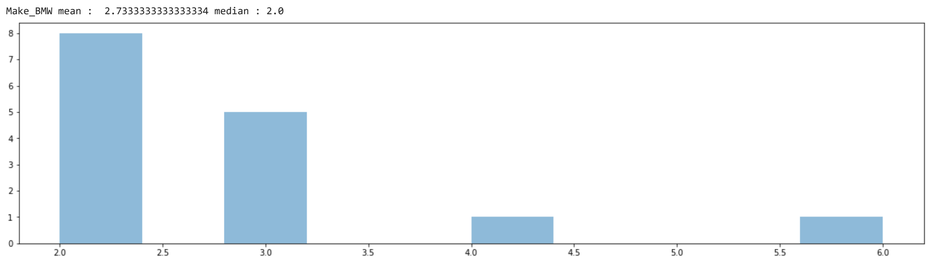
In [89]:
```
meanBrand =  {}
medianBrand = {}
```

In [90]:
```
for i in range(19):
    data_brand = dataset[dataset[make[i]]==1]
    fig, ax = plt.subplots(1, 1, figsize=(20, 5))
    print(str(make[i]) + " mean :  " +  str(np.mean(data_brand['VehiclePrice'])) + " median : "
          +str(np.median(data_brand['VehiclePrice'])))

    meanBrand[make[i]] = np.mean(data_brand['VehiclePrice'])
    medianBrand[make[i]] =  np.median(data_brand['VehiclePrice'])

    pyplot.hist( data_brand['VehiclePrice'], alpha=0.5, label='Fraud')
    pyplot.show()
```

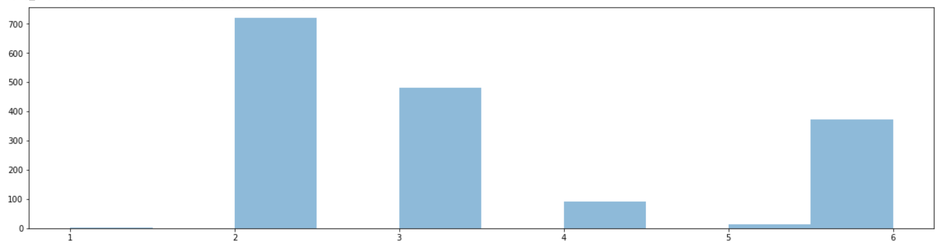
```
Make_Accura mean :  3.8728813559322033 median : 3.0
```



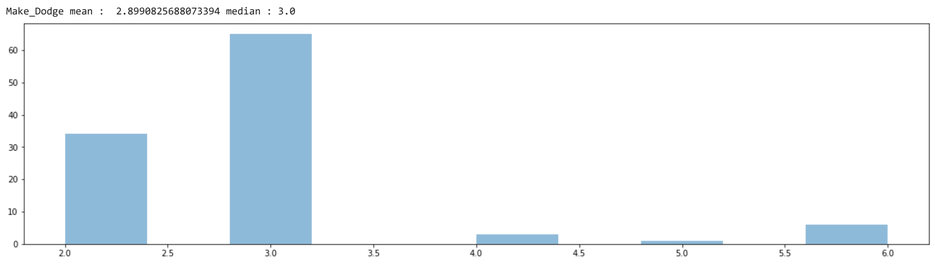
```
Make_BMW mean :  2.7333333333333334 median : 2.0
```



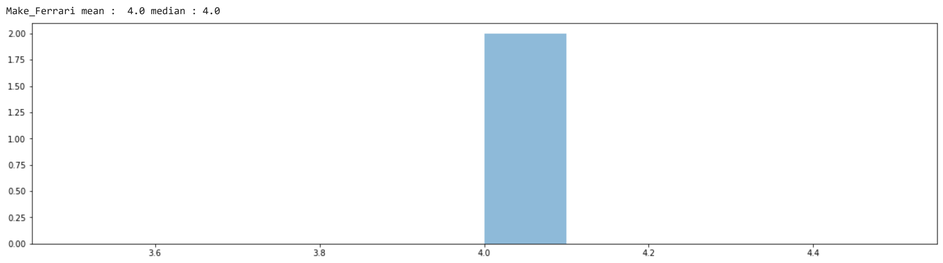
```
Make_Chevrolet mean :  3.3016061867935753 median : 3.0
```



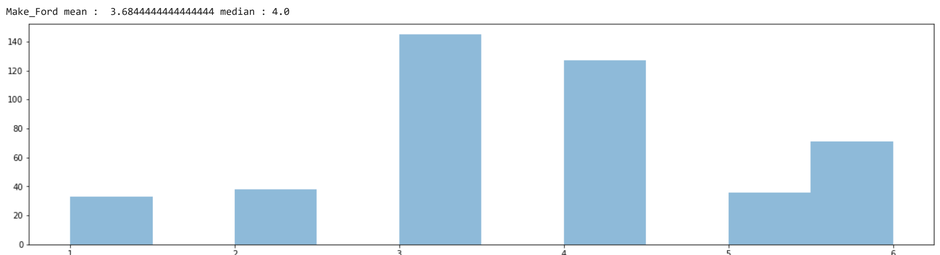
```
Make_Dodge mean :  2.8990825688073394 median : 3.0
```



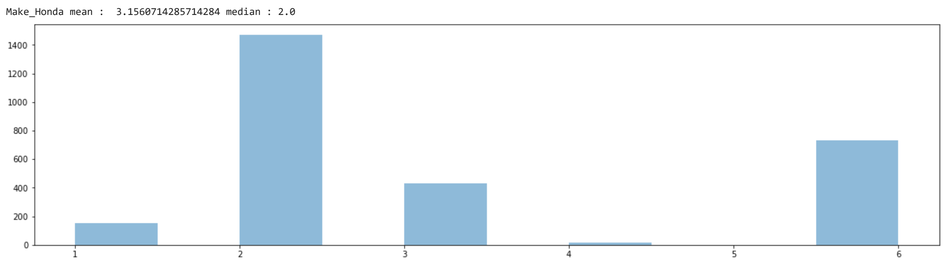
```
Make_Ferrari mean :  4.0 median : 4.0
```



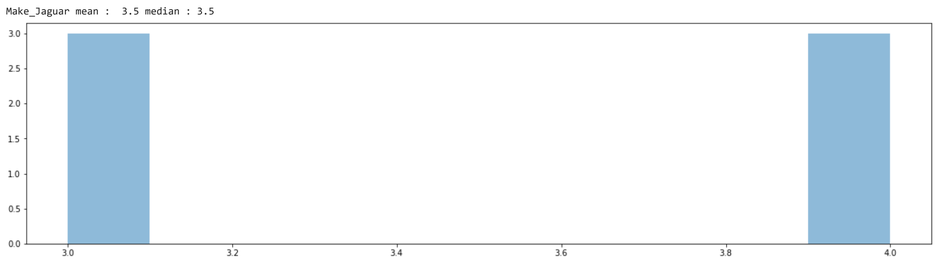
```
Make_Ford mean :  3.6844444444444444 median : 4.0
```



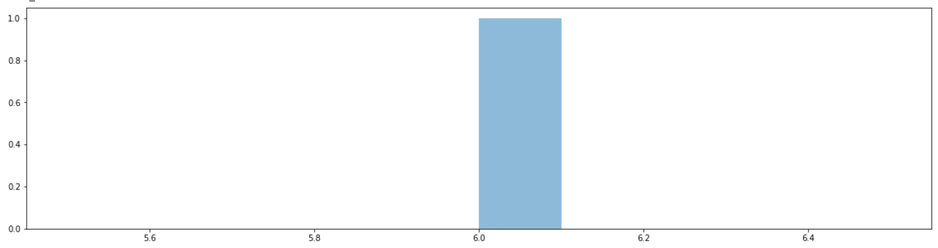
```
Make_Honda mean :  3.1560714285714284 median : 2.0
```



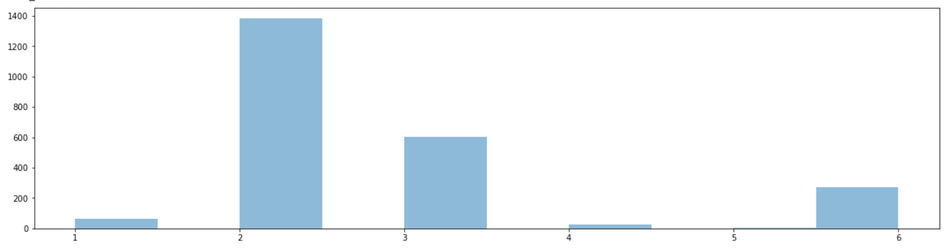
```
Make_Jaguar mean :  3.5 median : 3.5
```



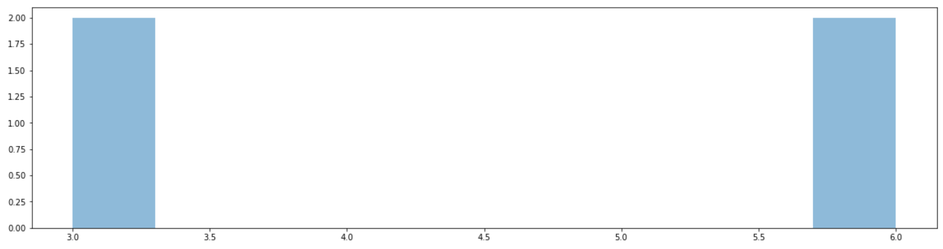
```
Make_Lexus mean :  6.0 median : 6.0
```



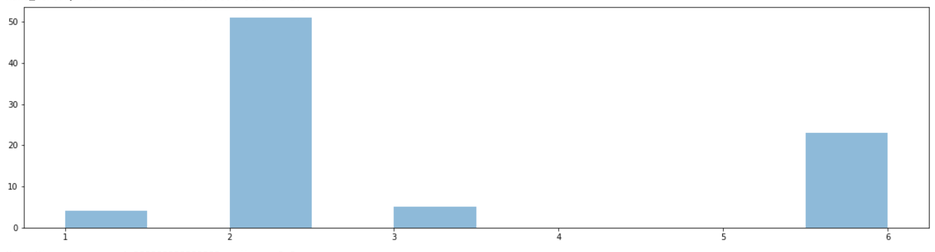
```
Make_Mazda mean :  2.7187765505522514 median : 2.0
```



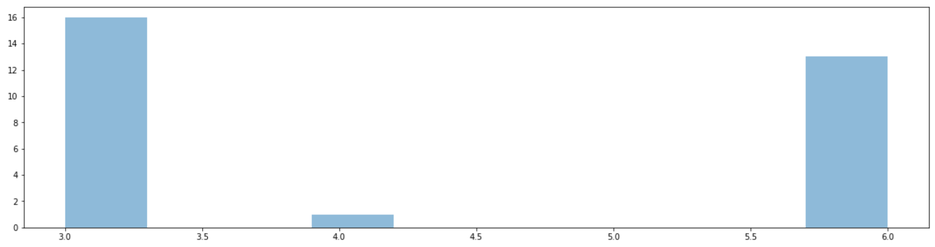
```
Make_Mecedes mean :  4.5 median : 4.5
```



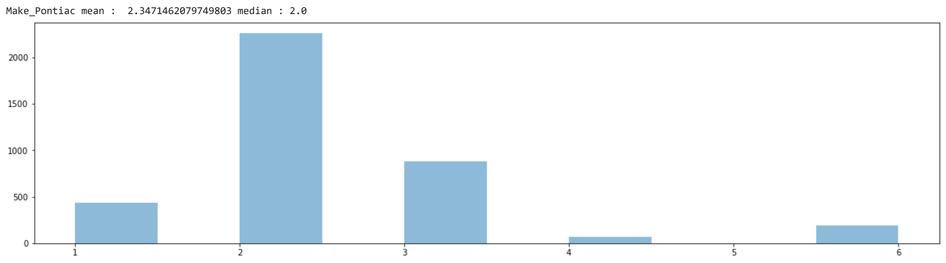
```
Make_Mercury mean :  3.1204819277108435 median : 2.0
```



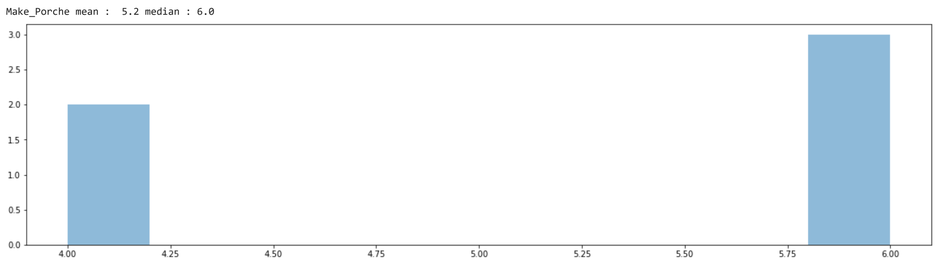
```
Make_Nisson mean :  4.333333333333333 median : 3.0
```



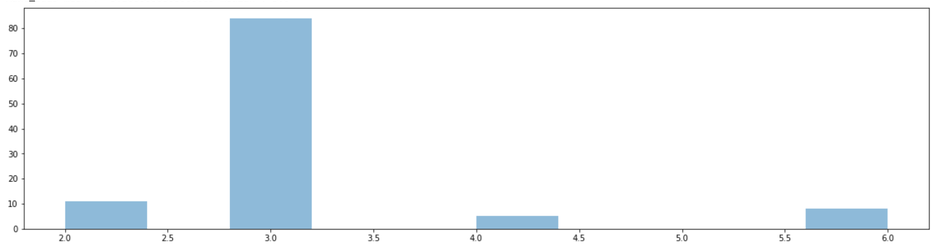
Make_Pontiac mean : 2.3471462079749803 median : 2.0



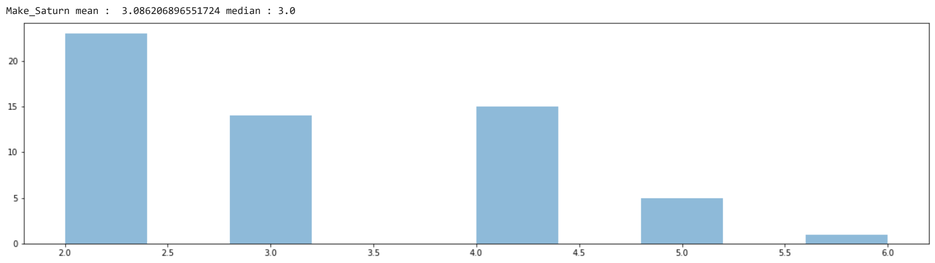
Make_Porche mean : 5.2 median : 6.0



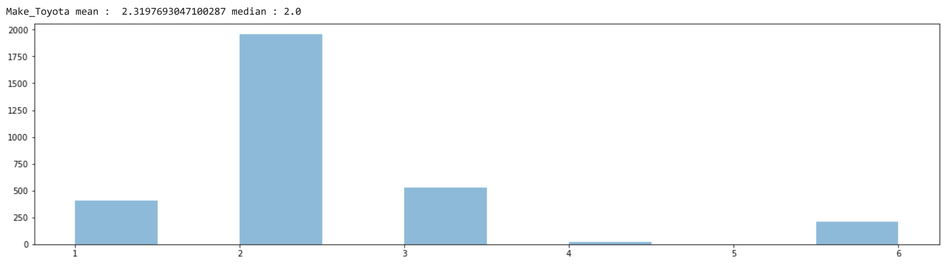
Make_Saab mean : 3.1666666666666665 median : 3.0



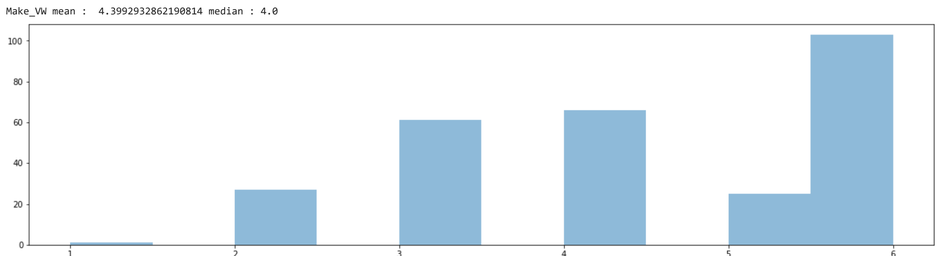
Make_Saturn mean : 3.086206896551724 median : 3.0



Make_Toyota mean : 2.3197693047100287 median : 2.0



Make_VW mean : 4.3992932862190814 median : 4.0



In [91]:
```
map_median = {}
map_mean = {}
for brand in make:
    brand_org = brand[5:]
    map_median[brand_org] = medianBrand[brand]
    map_mean[brand_org] = meanBrand[brand]
```

In [92]:
```
map_median
```

Out[92]:
```
{'Accura': 3.0,
 'BMW': 2.0,
 'Chevrolet': 3.0,
 'Dodge': 3.0,
 'Ferrari': 4.0,
 'Ford': 4.0,
 'Honda': 2.0,
 'Jaguar': 3.5,
 'Lexus': 6.0,
 'Mazda': 2.0,
 'Mecedes': 4.5,
 'Mercury': 2.0,
 'Nisson': 3.0,
 'Pontiac': 2.0,
 'Porche': 6.0,
 'Saab': 3.0,
 'Saturn': 3.0,
 'Toyota': 2.0,
 'VW': 4.0}
```

In [93]:
```
dataset['median_brand']=orginal.Make.map(map_median)
dataset['mean_brand']=orginal.Make.map(map_mean)
```

In [94]:
```
ordinalAdd.append('median_brand')
ordinalAdd.append('mean_brand')
```

3.Wealth

In [95]:
```
dataset['AgeOfVehicle'].unique()
```

Out[95]:
```
array([3, 6, 7, 9, 5, 1, 4, 2], dtype=int64)
```

In [96]:
```
dataset['NumberOfCars'].unique()
```

Out[96]:
```
array([ 3.5,  1. ,  2. ,  6.5, 10. ])
```

In [97]:
```
dataset['wealth1'] = dataset['NumberOfCars'] * (dataset['VehiclePrice']/dataset['AgeOfVehicle'])
```

In [98]:
```
ordinalAdd.append('wealth1')
```

In [99]:
```
dataset['wealth2'] = dataset['NumberOfCars'] * dataset['VehiclePrice']
```

In [100…
```
ordinalAdd.append('wealth2')
```

4.RatioPolicy

In [101…
```
dataset['ratioPolicy'] = dataset['AgeOfVehicle'] / dataset['AgeOfPolicyHolder']
```

In [102…
```
ordinalAdd.append('ratioPolicy')
```

In [103…
```
len(ordinalAdd)
```

Out[103…
```
19
```

In [104…
```
ordinalAdd
```

Out[104…
```
['Month',
 'DayOfWeek',
 'DayOfWeekClaimed',
 'MonthClaimed',
 'VehiclePrice',
 'Days_Policy_Accident',
 'Days_Policy_Claim',
 'PastNumberOfClaims',
 'AgeOfVehicle',
 'AgeOfPolicyHolder',
 'NumberOfSuppliments',
 'AddressChange_Claim',
 'NumberOfCars',
 'ratioRepNumber',
 'median_brand',
 'mean_brand',
 'wealth1',
 'wealth2',
 'ratioPolicy']
```

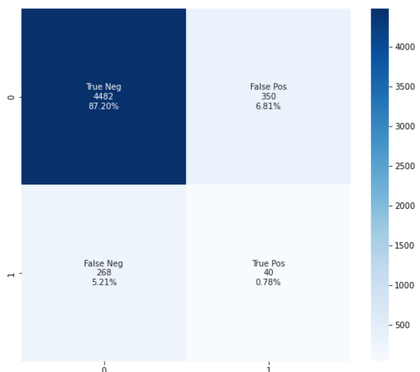
In [105…
```
ordinalAdd.append(target)
```

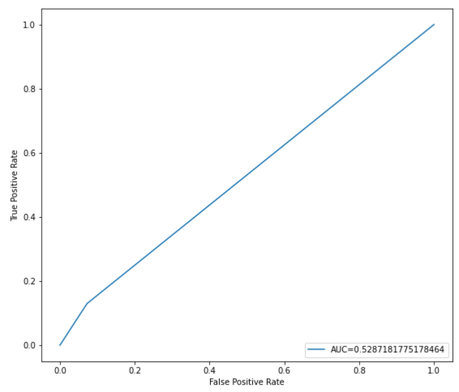
In [106…
```
ordinalDataAdd = dataset[ordinalAdd]
```

In [107…
```
DataAdd = Models_Startified(ordinalDataAdd,'FraudFound_P',3)
DataAdd.DT(True)
```

```
DecisionTree.....................................

List of possible accuracy: dict_values([0.8797665369649805, 0.867704280155642, 0.8744892002335085])

Maximum Accuracy That can be obtained from this model is: 87.97665369649805 %

Minimum Accuracy: 86.7704280155642 %

Overall Accuracy: 87.3986672451377 %

Standard Deviation is: 0.0060468094099108 5

List of possible F1-score: dict_values([0.1146131805157593, 0.06593406593406594, 0.06926406926406926])

Maximum F1-score That can be obtained from this model is: 11.46131805157593 %

Minimum F1-score: 6.593406593406594 %

Overall F1-score: 8.327043857129816 %
```

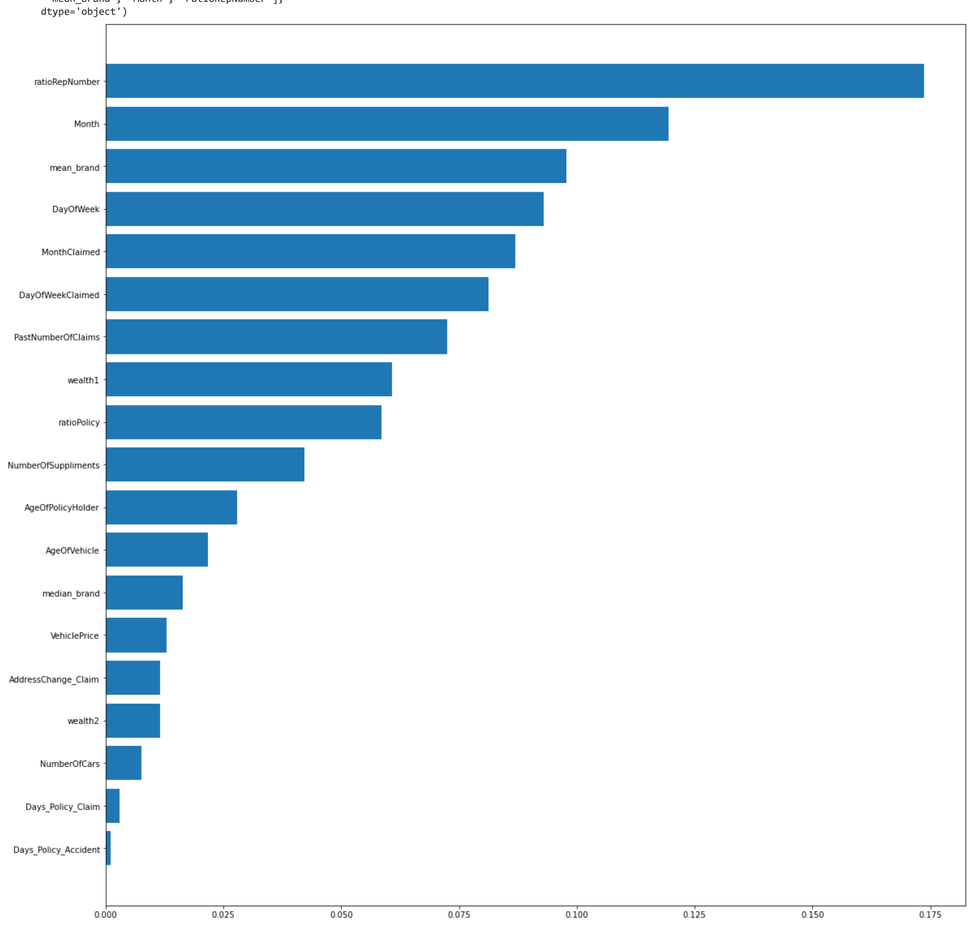
```
Standard Deviation is: 0.027194628789381753
```






```
              precision    recall  f1-score   support

         Yes       0.94      0.93      0.94      4832
          No       0.10      0.13      0.11       308

    accuracy                           0.88      5140
   macro avg       0.52      0.53      0.53      5140
weighted avg       0.89      0.88      0.89      5140
```

```
Feature Importance.....................................

19
Index(['Days_Policy_Accident', 'Days_Policy_Claim', 'NumberOfCars', 'wealth2',
       'AddressChange_Claim', 'VehiclePrice', 'median_brand', 'AgeOfVehicle',
       'AgeOfPolicyHolder', 'NumberOfSuppliments', 'ratioPolicy', 'wealth1',
       'PastNumberOfClaims', 'DayOfWeekClaimed', 'MonthClaimed', 'DayOfWeek',
       'mean_brand', 'Month', 'ratioRepNumber'],
      dtype='object')
```



It looks like defines wealth, considering age of vehicle was better choice

In [108…
```
dataset.drop('wealth2', inplace=True, axis=1)
ordinalAdd.remove('wealth2')
```

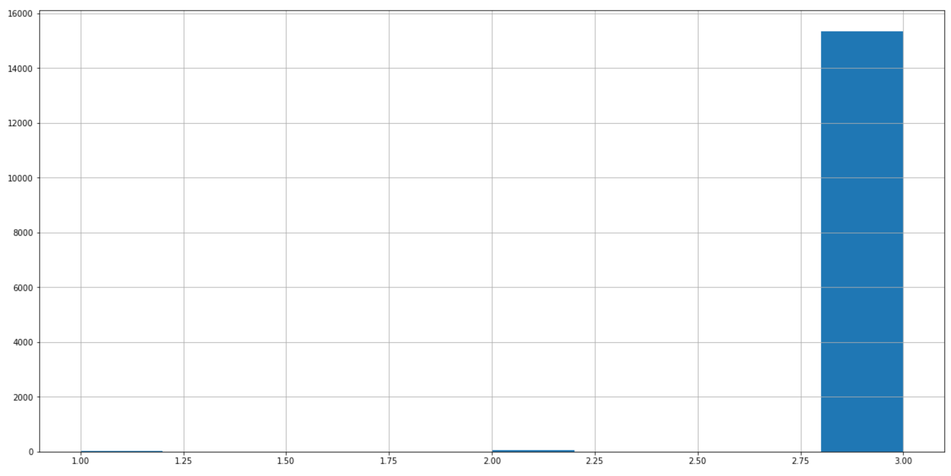
In [109…
```
dataset.drop('median_brand', inplace=True, axis=1)
ordinalAdd.remove('median_brand')
```

In [110…
```
ordinalAdd
```

Out[110…
```
['Month',
 'DayOfWeek',
 'DayOfWeekClaimed',
 'MonthClaimed',
 'VehiclePrice',
 'Days_Policy_Accident',
 'Days_Policy_Claim',
 'PastNumberOfClaims',
 'AgeOfVehicle',
 'AgeOfPolicyHolder',
 'NumberOfSuppliments',
 'AddressChange_Claim',
 'NumberOfCars',
 'ratioRepNumber',
 'mean_brand',
 'wealth1',
 'ratioPolicy',
 'FraudFound_P']
```

In [111…
```
dataset['Days_Policy_Claim'].hist(figsize=(20,10))
```

Out[111…
```
<AxesSubplot:>
```

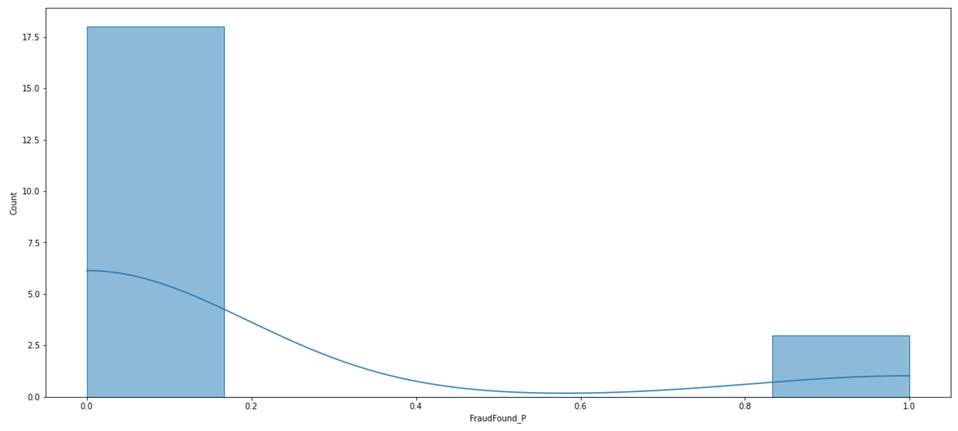


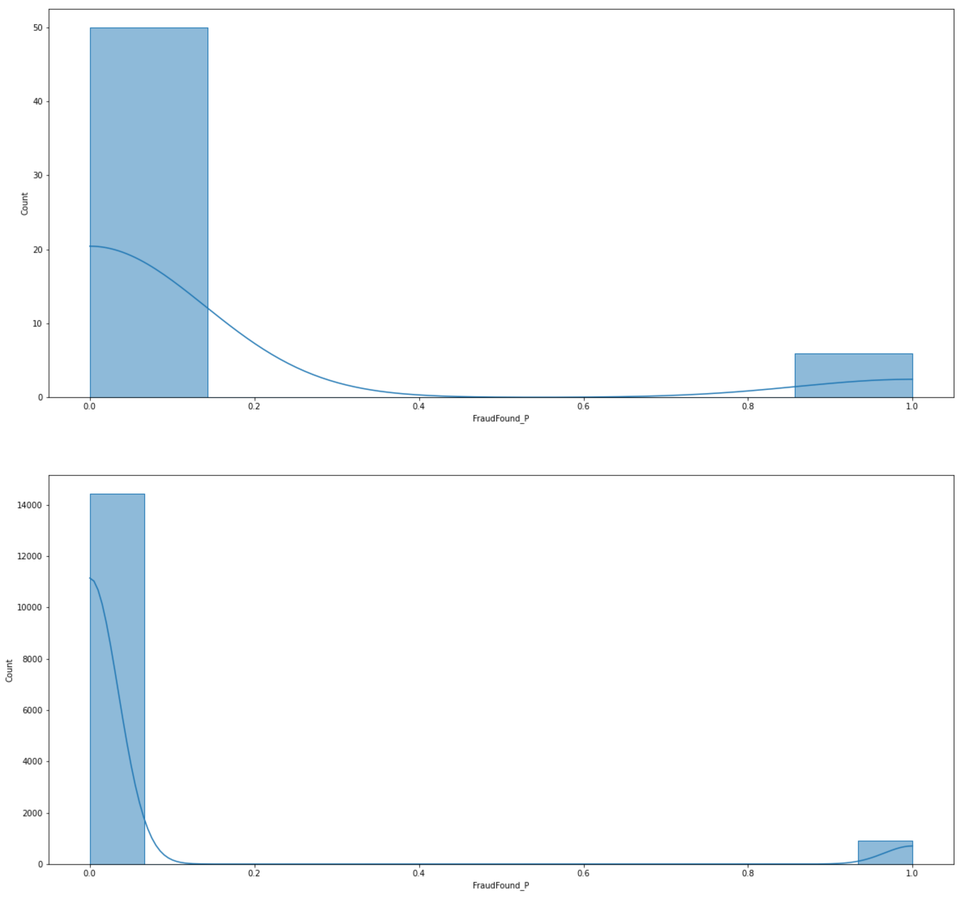
In [112…
```
dataset['Days_Policy_Claim'].unique()
```

Out[112…
```
array([3, 2, 1], dtype=int64)
```

In [113…
```
fig, ax = plt.subplots(3, 1, figsize=(20, 30))
sns.histplot(x=dataset[dataset['Days_Policy_Claim'] == 1].loc[:,target], data=dataset[dataset['Days_Policy_Claim'] == 1], kde=True, element="step",ax=ax[0])
sns.histplot(x=dataset[dataset['Days_Policy_Claim'] == 2].loc[:,target], data=dataset[dataset['Days_Policy_Claim'] == 2], kde=True, element="step",ax=ax[1])
sns.histplot(x=dataset[dataset['Days_Policy_Claim'] == 3].loc[:,target], data=dataset[dataset['Days_Policy_Claim'] == 3], kde=True, element="step",ax=ax[2])
```

Out[113…
```
<AxesSubplot:xlabel='FraudFound_P', ylabel='Count'>
```





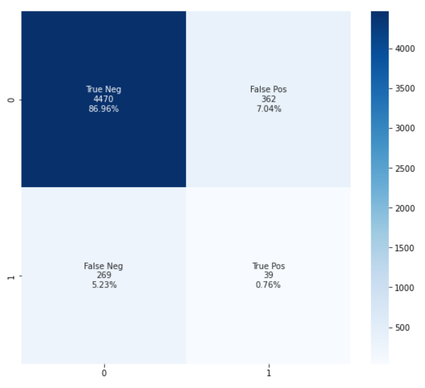
In [114…
```
dataset.drop('Days_Policy_Claim', inplace=True, axis=1)
```

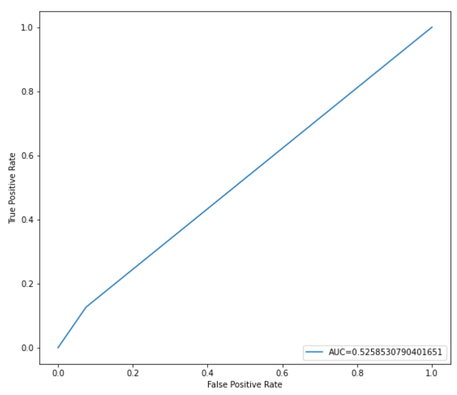
In [115…
```
ordinalAdd.remove('Days_Policy_Claim')
```

In [116…
```
datasetOrdinalAdd = dataset[ordinalAdd]
```

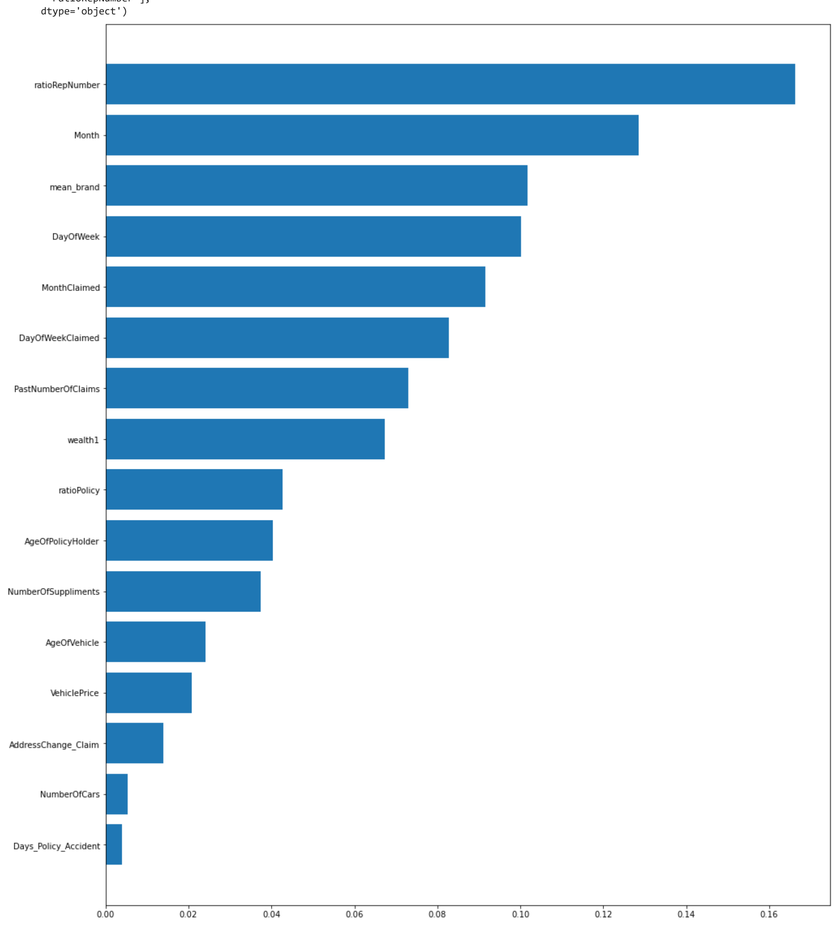
In [117…
```
modelordinalDataAdd = Models_Startified(datasetOrdinalAdd,'FraudFound_P',3)
modelordinalDataAdd.DT(True)
```

```
DecisionTree.....................................

List of possible accuracy: dict_values([0.8772373540856031, 0.8729571984435798, 0.876629694493092])

Maximum Accuracy That can be obtained from this model is: 87.72373540856032 %

Minimum Accuracy: 87.29571984435798 %

Overall Accuracy: 87.56080823407582 %

Standard Deviation is: 0.00231575076861328

List of possible F1-score: dict_values([0.11001410437235543, 0.0917941585535466, 0.10704225352112677])

Maximum F1-score That can be obtained from this model is: 11.001410437235542 %

Minimum F1-score: 9.17941585535466 %

Overall F1-score: 10.29501721490096 %

Standard Deviation is: 0.00977499124690675
```

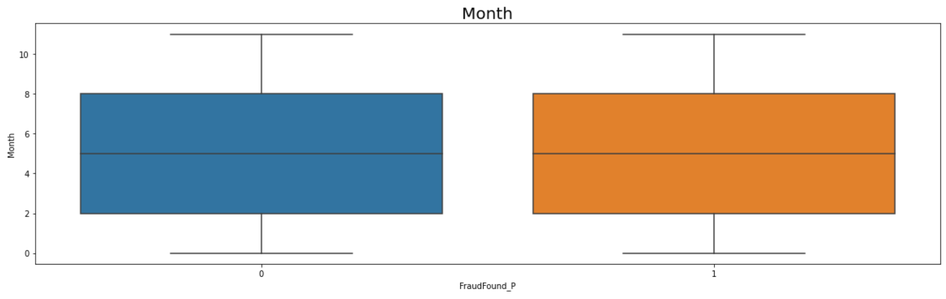


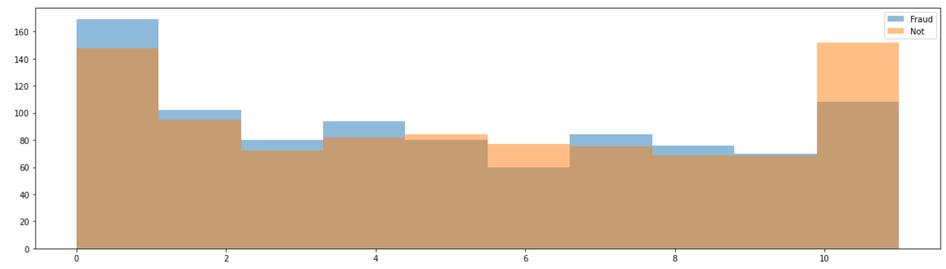


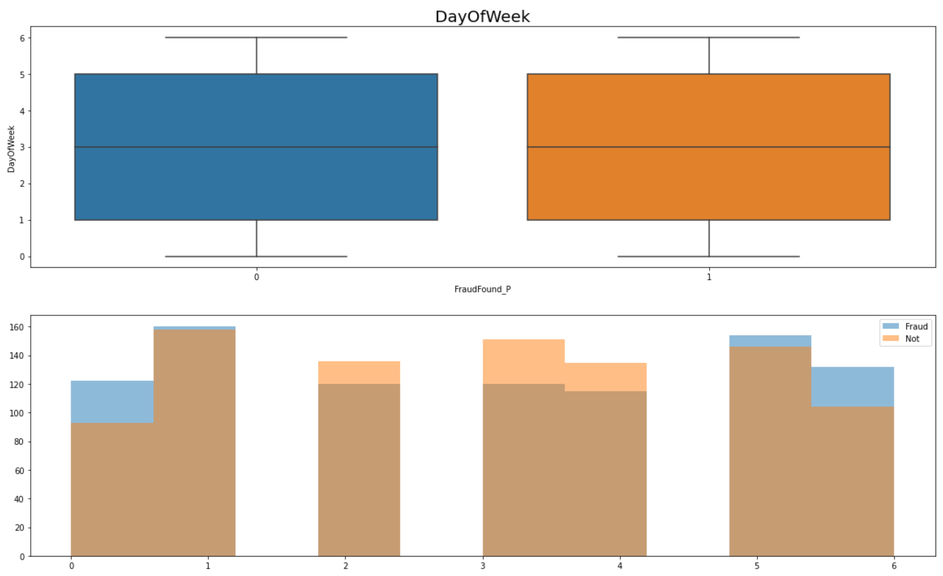

```
              precision    recall  f1-score   support

         Yes       0.94      0.93      0.93      4832
          No       0.10      0.13      0.11       308

    accuracy                           0.88      5140
   macro avg       0.52      0.53      0.52      5140
weighted avg       0.89      0.88      0.88      5140


Feature Importance.................................

16
Index(['Days_Policy_Accident', 'NumberOfCars', 'AddressChange_Claim',
       'VehiclePrice', 'AgeOfVehicle', 'NumberOfSuppliments',
       'AgeOfPolicyHolder', 'ratioPolicy', 'wealth1', 'PastNumberOfClaims',
       'DayOfWeekClaimed', 'MonthClaimed', 'DayOfWeek', 'mean_brand', 'Month',
       'ratioRepNumber'],
      dtype='object')
```

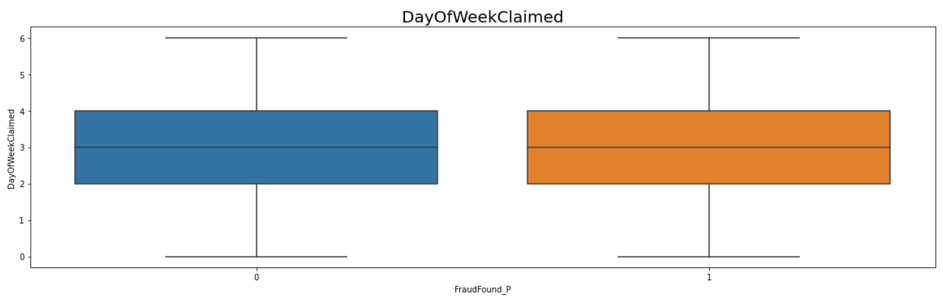


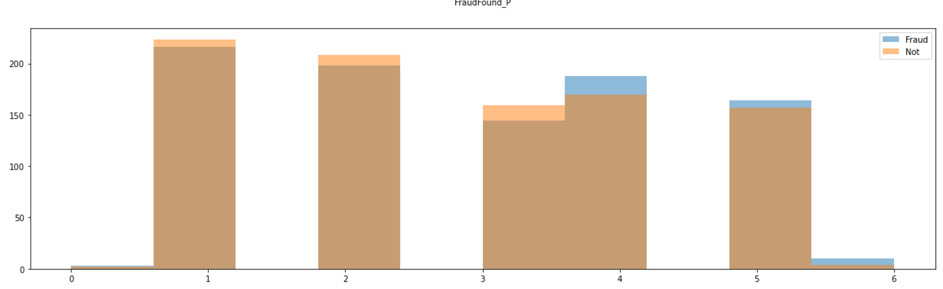
In [118…
```
for feature in ordinalAdd:
    compare(feature,dataset)
```

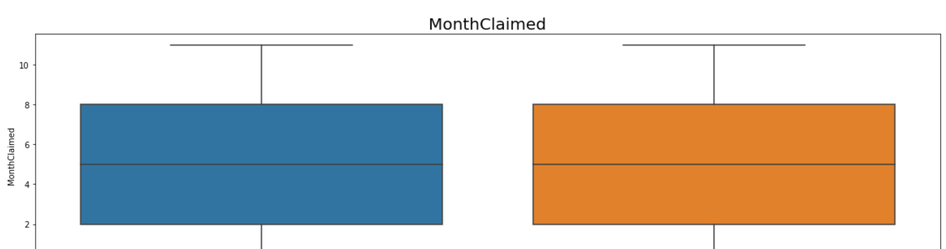


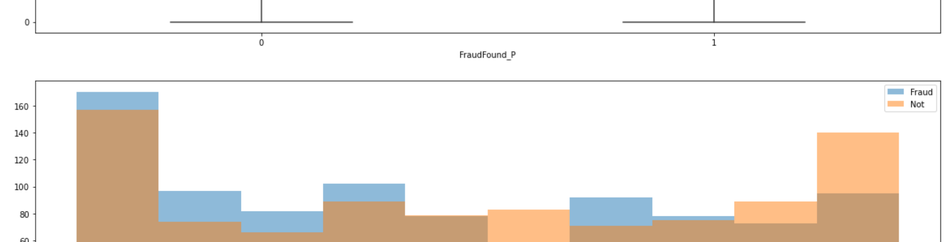




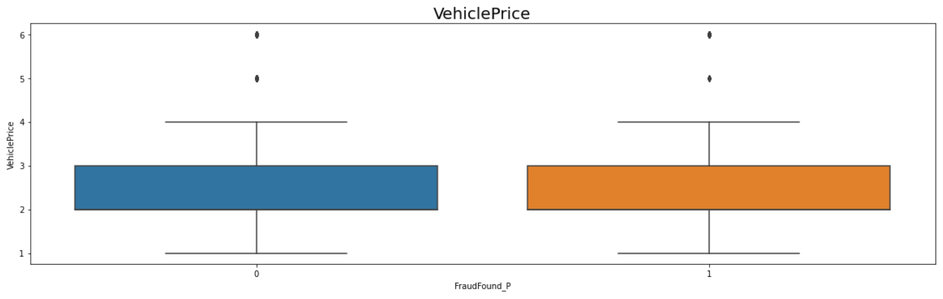


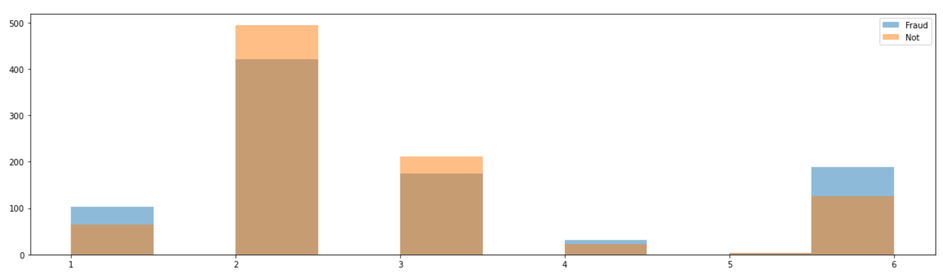


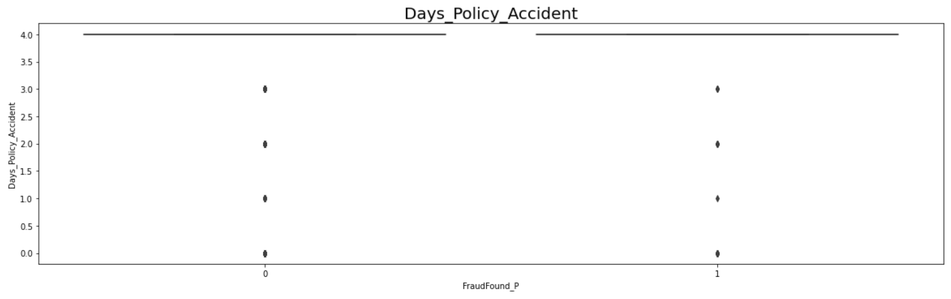


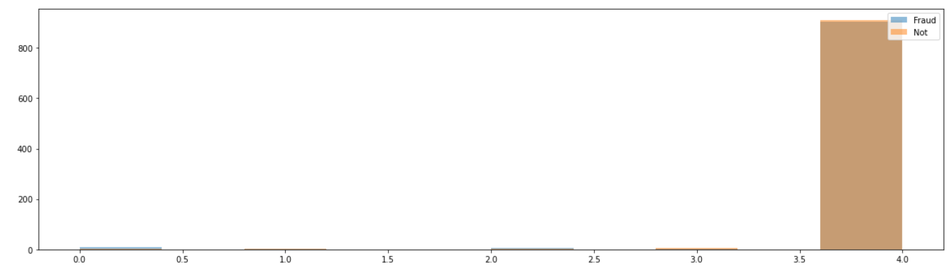


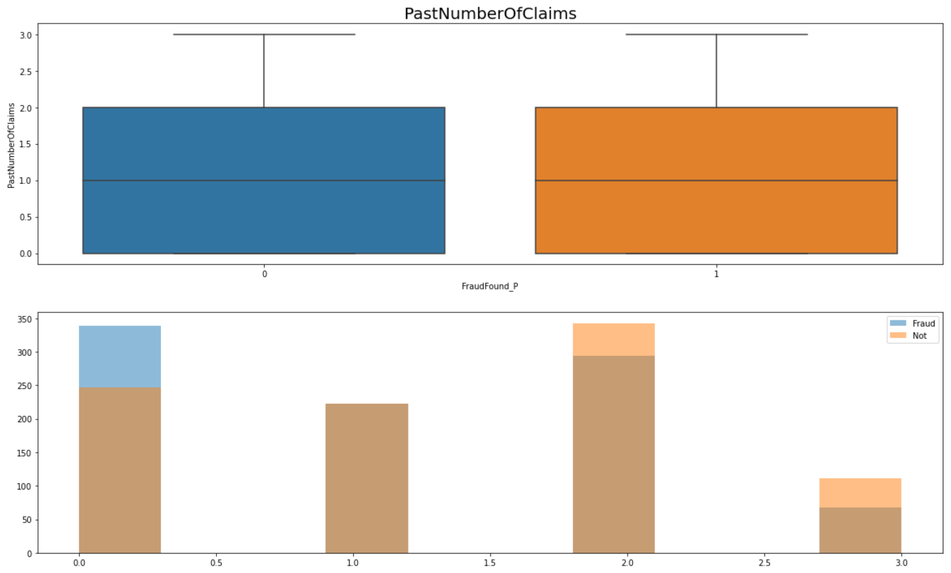
VehiclePrice



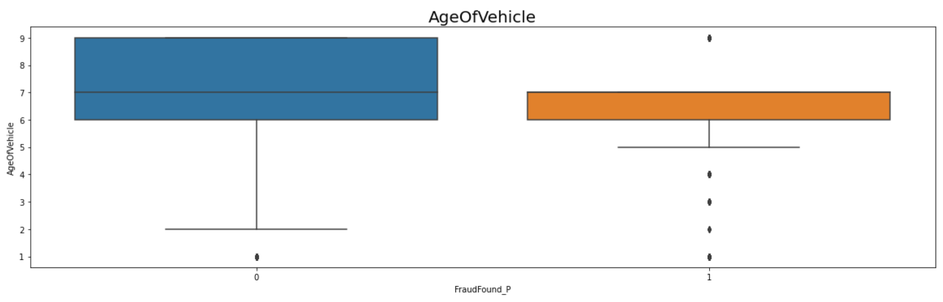


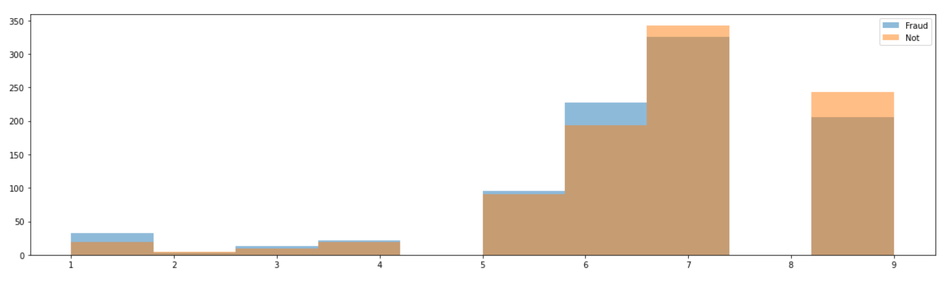

Days_Policy_Accident
Days_Policy_Accident
FraudFound_P

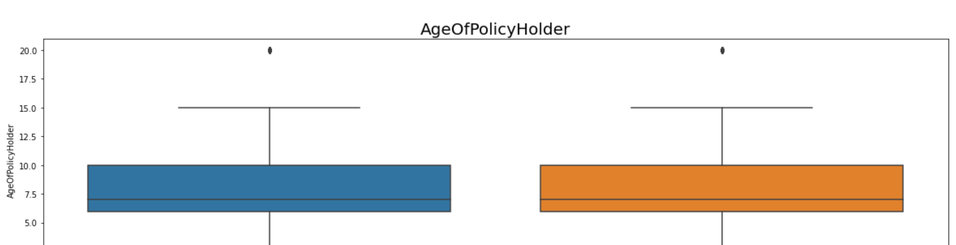

Fraud
Not

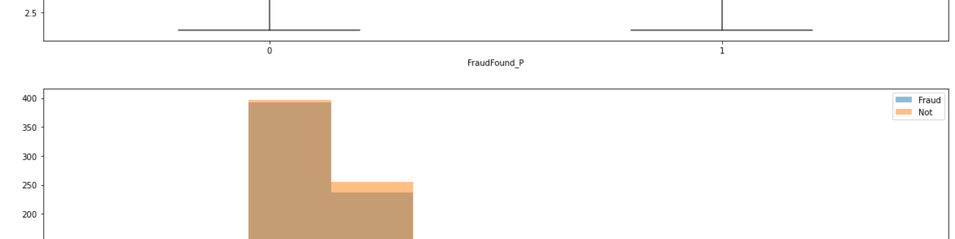

PastNumberOfClaims
PastNumberOfClaims
FraudFound_P

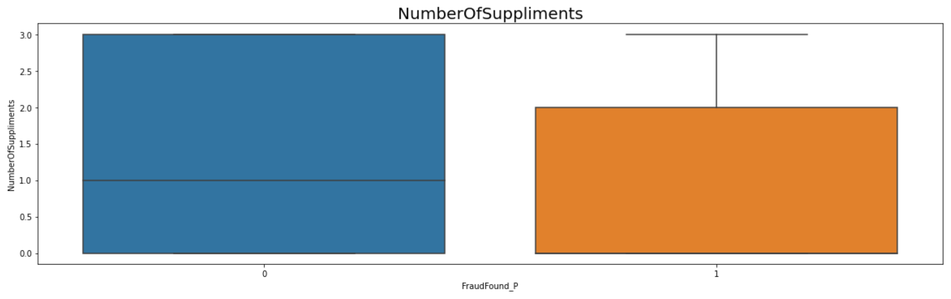
Fraud
Not

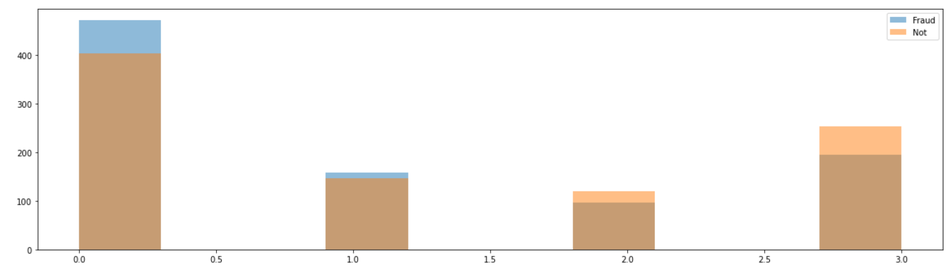

AgeOfVehicle
AgeOfVehicle
FraudFound_P

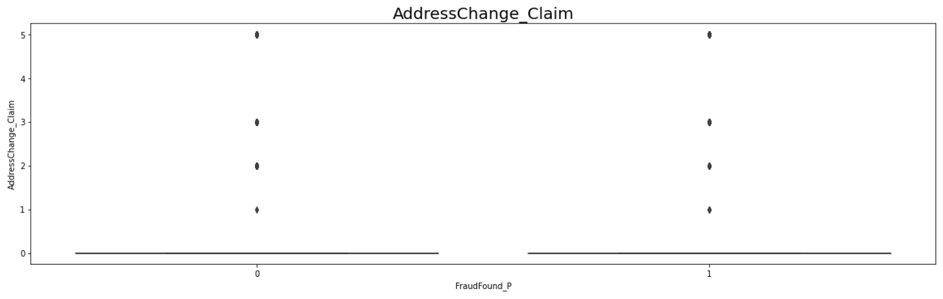

Fraud
Not

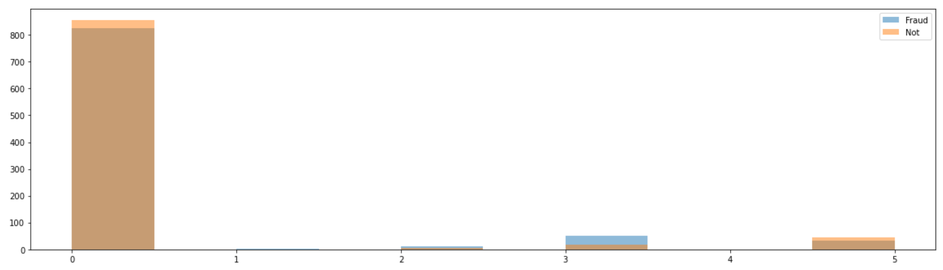

AgeOfPolicyHolder
AgeOfPolicyHolder
FraudFound_P

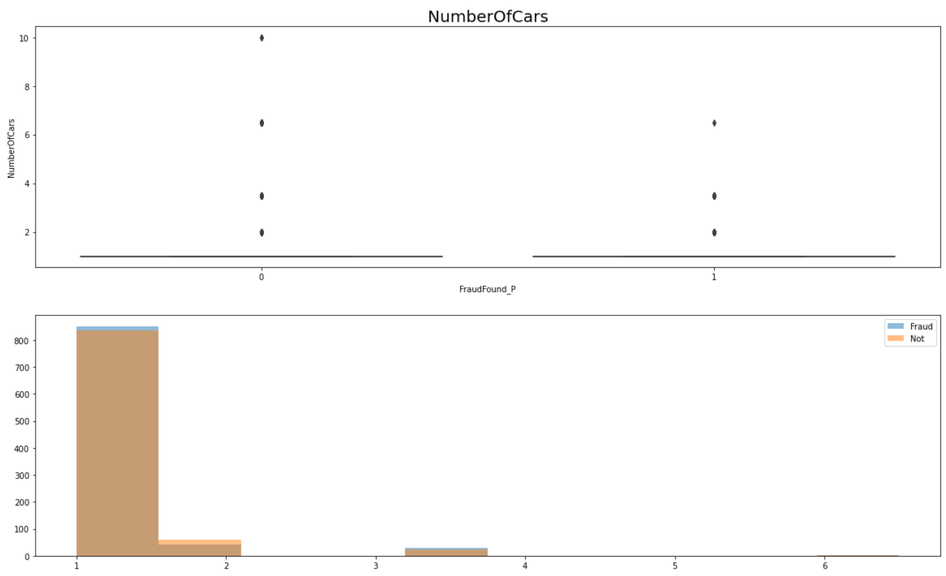

Fraud
Not


NumberOfSuppliments
NumberOfSuppliments
FraudFound_P

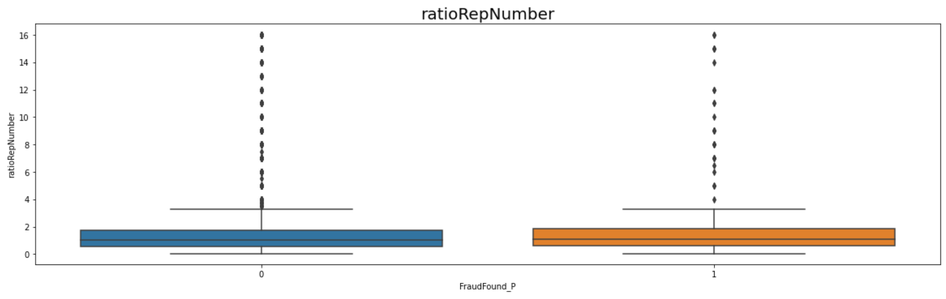

Fraud
Not

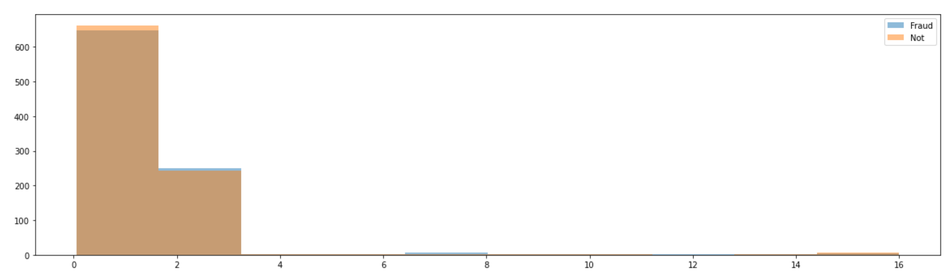

AddressChange_Claim
AdressChange_Claim
FraudFound_P

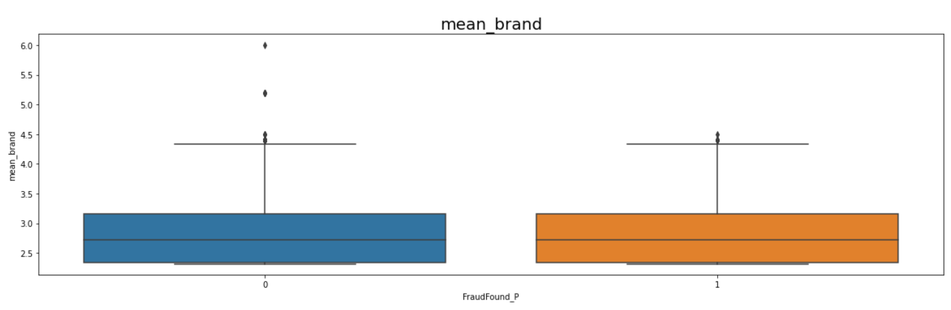

Fraud
Not

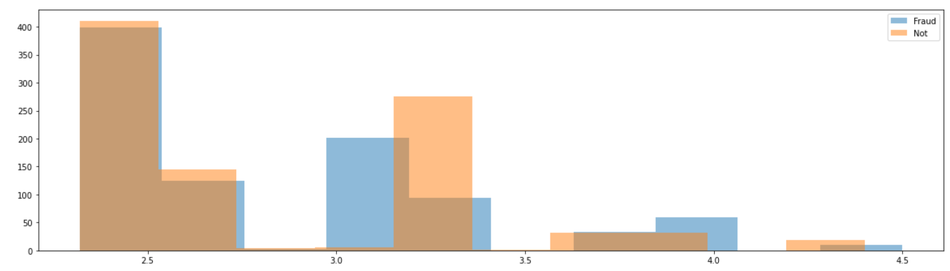

NumberOfCars
FraudFound_P

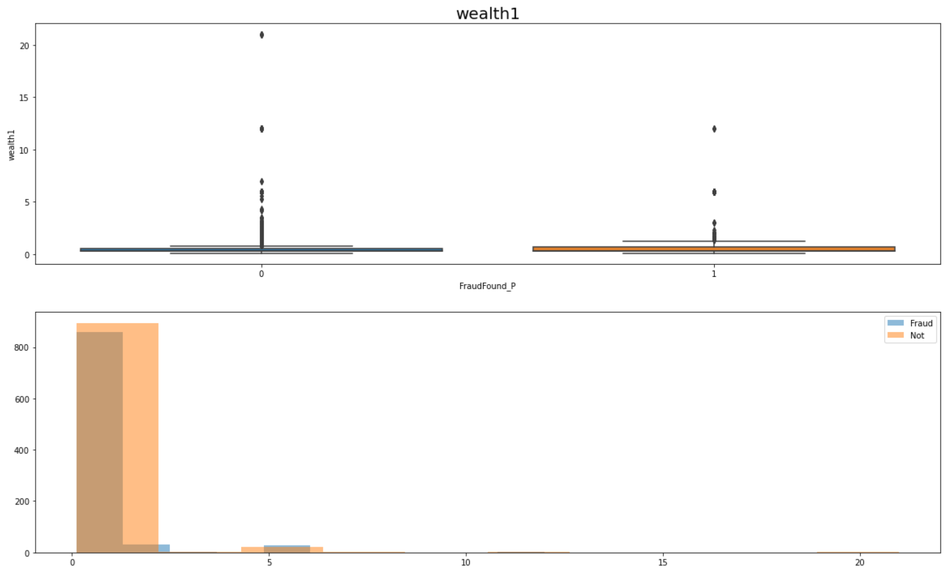
Fraud
Not


ratioRepNumber
FraudFound_P

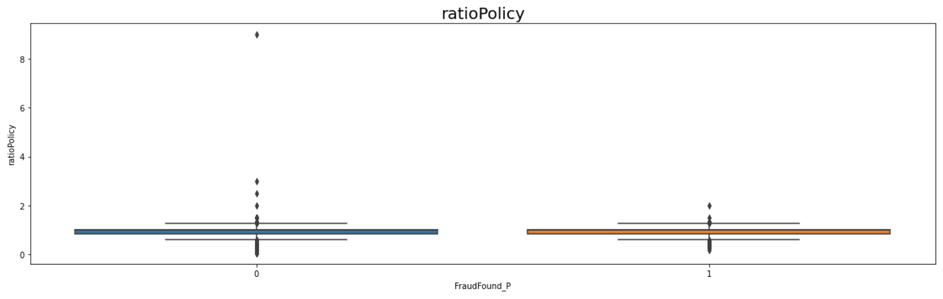

Fraud
Not

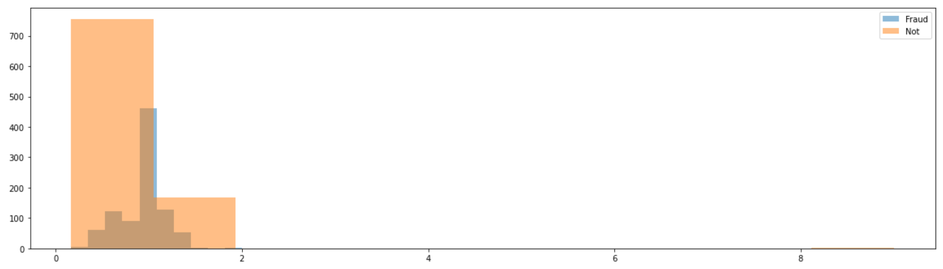

mean_brand
FraudFound_P

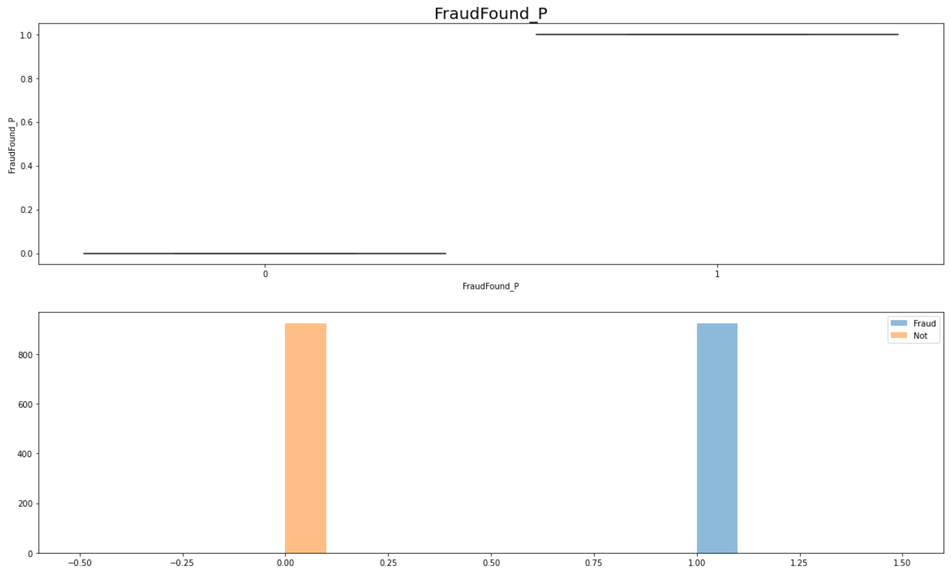

Fraud
Not


wealth1
FraudFound_P

Fraud
Not







In [119…

```
num_1 = len(dataset[dataset[target]==1])
num_0 = len(dataset[dataset[target]==0])
undersampled_dataset = pd.concat([dataset[dataset[target]==0].sample(num_1) ,dataset[dataset[target]==1] ])
fraud = undersampled_dataset[undersampled_dataset['FraudFound_P'] == 1]
```

Test new datast

In [221…

```
dataset
```

Out[221…

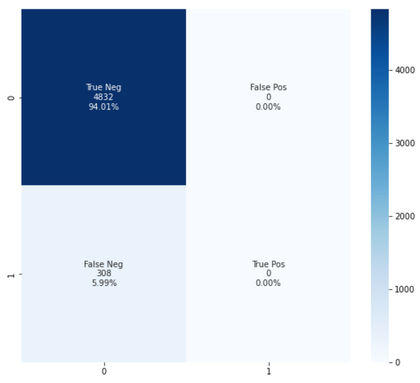
	Month	WeekOfMonth	DayOfWeek	DayOfWeekClaimed	MonthClaimed	WeekOfMonthClaimed	Age	VehiclePrice	FraudFound_P	RepNumber	Deductible	DriverRating	Days_Policy_Accident	PastNumberOfClaims	AgeOfVehicle	AgeOfPolicyHolder	NumberOfSuppliments	AddressChange_Claim	NumberOfCars	Year	VehicleCategory_Sedan	VehicleCategory_Sport	VehicleCategory_Utility	Fault_Policy Holder	Fault_Third Party	Make_Accura	Make_BMW	Make_Chevrolet	Make_Dodge	Make_Ferrari	Ma
0	11	5	4	2.0	0.0	1	2.1	6	0	12	3.0	1	4	0	3	5	0	2	3.5	0	0	1	0	1	0	0	0	0	0	0	
1	0	3	4	1.0	0.0	4	3.4	6	0	15	4.0	4	4	0	6	6	0	0	1.0	0	0	1	0	1	0	0	0	0	0	0	
2	9	5	5	3.0	10.0	2	4.7	6	0	7	4.0	3	4	1	7	10	0	0	1.0	0	0	1	0	1	0	0	0	0	0	0	
3	5	2	6	5.0	6.0	1	6.5	2	0	4	4.0	2	4	1	9	15	3	0	1.0	0	0	1	0	0	1	0	0	0	0	0	
4	0	5	1	2.0	1.0	2	2.7	6	0	3	4.0	1	4	0	5	6	0	0	1.0	0	0	1	0	0	1	0	0	0	0	0	
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	
15415	10	4	5	2.0	10.0	5	3.5	2	1	5	4.0	4	4	2	6	6	0	0	1.0	2	1	0	0	1	0	0	0	0	0	0	
15416	10	5	3	5.0	11.0	1	3.0	3	0	11	4.0	3	4	3	6	6	3	0	3.5	2	0	1	0	1	0	0	0	0	0	0	
15417	10	5	3	5.0	11.0	1	2.4	2	1	4	4.0	4	4	3	5	5	1	0	1.0	2	1	0	0	1	0	0	0	0	0	0	
15418	11	1	1	3.0	11.0	2	3.4	2	0	6	4.0	4	4	0	2	6	3	0	1.0	2	1	0	0	0	1	0	0	0	0	0	
15419	11	2	4	3.0	11.0	3	2.1	2	1	3	4.0	4	4	0	5	5	1	0	1.0	2	1	0	0	1	0	0	0	0	0	0	

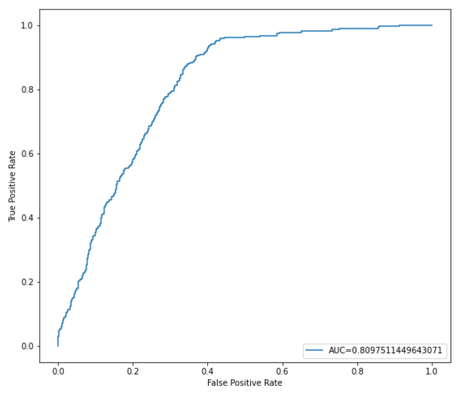
15419 rows × 76 columns

In [222…

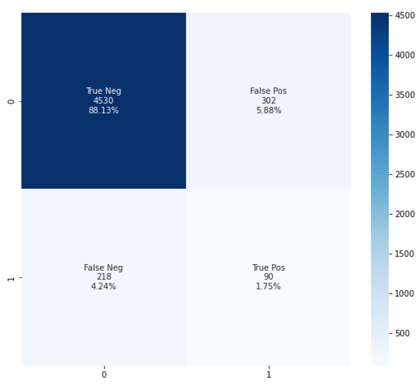
```
modelFeatureAdding = Models_Startified(dataset,'FraudFound_P',3)
modelFeatureAdding.testClassification()
```

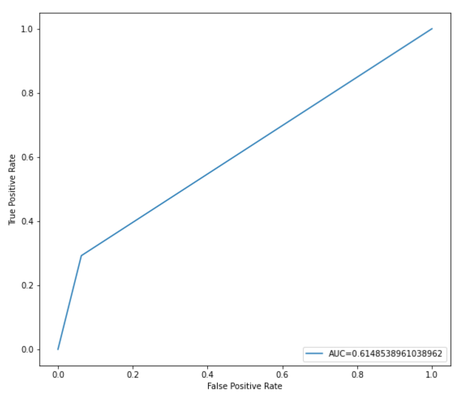
```
LogisticRegression.................................

List of possible accuracy: dict_values([0.9400778210116731, 0.9400778210116731, 0.9400661607316598])

Maximum Accuracy That can be obtained from this model is: 94.00778210116731 %

Minimum Accuracy: 94.00661607316599 %

Overall Accuracy: 94.00739342516687 %

Standard Deviation is: 6.73206580451369e-06

List of possible F1-score: dict_values([0.0, 0.0, 0.0])

Maximum F1-score That can be obtained from this model is: 0.0 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.0 %

Standard Deviation is: 0.0
```





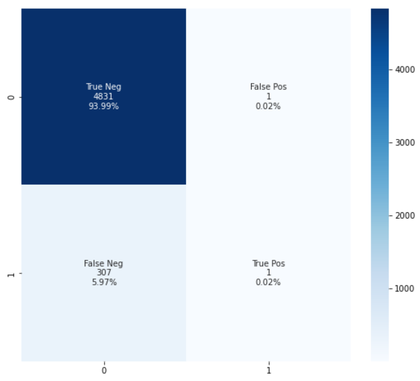

```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       1.00      0.00      0.00       308

    accuracy                           0.94      5140
   macro avg       0.97      0.50      0.48      5140
weighted avg       0.94      0.94      0.91      5140


DecisionTree.......................................

List of possible accuracy: dict_values([0.8988326848249028, 0.9056420233463035, 0.8877213465654796])

Maximum Accuracy That can be obtained from this model is: 90.56420233463035 %

Minimum Accuracy: 88.77213465654796 %

Overall Accuracy: 89.73986849122286 %

Standard Deviation is: 0.009045989768005048

List of possible F1-score: dict_values([0.2571428571428571, 0.22893481717011127, 0.15519765739385066])

Maximum F1-score That can be obtained from this model is: 25.71428571428571 %

Minimum F1-score: 15.519765739385067 %

Overall F1-score: 21.375844390227304 %

Standard Deviation is: 0.05263979167074821
```

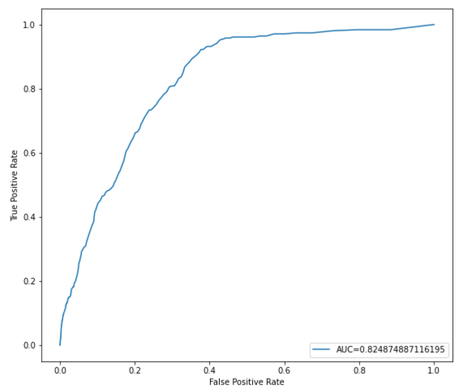




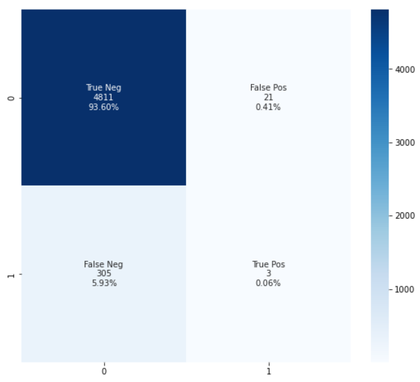

```
              precision    recall  f1-score   support

         Yes       0.95      0.94      0.95      4832
          No       0.23      0.29      0.26       308

    accuracy                           0.90      5140
   macro avg       0.59      0.61      0.60      5140
weighted avg       0.91      0.90      0.90      5140


RandomForest.......................................

List of possible accuracy: dict_values([0.9398832684824903, 0.9400778210116731, 0.9396769799571901])

Maximum Accuracy That can be obtained from this model is: 94.00778210116731 %

Minimum Accuracy: 93.967697995719 %
```

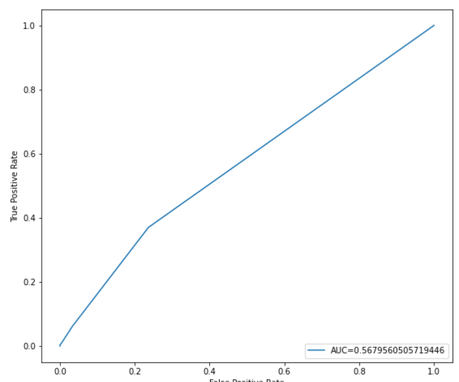
```
Overall Accuracy: 93.98793564837845 %

Standard Deviation is: 0.00020044915948980448

List of possible F1-score: dict_values([0.0, 0.0064516129032258064, 0.0])

Maximum F1-score That can be obtained from this model is: 0.6451612903225806 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.21505376344086022 %

Standard Deviation is: 0.0037248404463846824
```



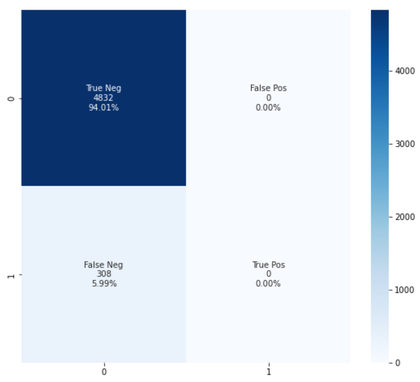


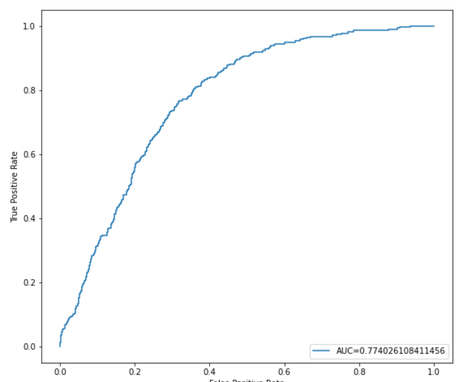

```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       0.50      0.00      0.01       308

    accuracy                           0.94      5140
   macro avg       0.72      0.50      0.49      5140
weighted avg       0.91      0.94      0.91      5140


KNN.....................................................

List of possible accuracy: dict_values([0.9365758754863813, 0.9365758754863813, 0.9369527145359019])

Maximum Accuracy That can be obtained from this model is: 93.6952714535902 %

Minimum Accuracy: 93.65758754863813 %

Overall Accuracy: 93.67014885028881 %

Standard Deviation is: 0.00021756812668186496

List of possible F1-score: dict_values([0.018072289156626505, 0.012121212121212123, 0.006134969325153735])

Maximum F1-score That can be obtained from this model is: 1.8072289156626504 %

Minimum F1-score: 0.6134969325153373 %

Overall F1-score: 1.2109490200997335 %

Standard Deviation is: 0.0059686685485358095
```






```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       0.12      0.01      0.02       308

    accuracy                           0.94      5140
   macro avg       0.53      0.50      0.49      5140
weighted avg       0.89      0.94      0.91      5140


SVC.....................................................

List of possible accuracy: dict_values([0.9400778210116731, 0.9400778210116731, 0.9402607511188947])

Maximum Accuracy That can be obtained from this model is: 94.02607511188947 %

Minimum Accuracy: 94.00778210116731 %

Overall Accuracy: 94.01387977140804 %

Standard Deviation is: 0.00010561474664727239

List of possible F1-score: dict_values([0.0, 0.0, 0.0])

Maximum F1-score That can be obtained from this model is: 0.0 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.0 %

Standard Deviation is: 0.0
```






```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       1.00      0.00      0.00       308

    accuracy                           0.94      5140
   macro avg       0.97      0.50      0.48      5140
weighted avg       0.94      0.94      0.91      5140


F1-Score.....................................

                    0          1
0        DecisionTree  25.714286
1                 KNN   1.807229
2        RandomForest   0.645161
3  LogisticRegression   0.000000
4                 SVC   0.000000

Accuracy.....................................

                    0          1
0                 SVC  94.026075
1  LogisticRegression  94.007782
2        RandomForest  94.007782
3                 KNN  93.695271
4        DecisionTree  90.564202
```

In [123…

```
def select_features(X_train, y_train, X_test, k_value='all'):
    fs = SelectKBest(score_func=chi2, k=k_value)
    fs.fit(X_train, y_train)
    X_train_fs = fs.transform(X_train)
    X_test_fs = fs.transform(X_test)
    return X_train_fs, X_test_fs, fs
```

Handle Imbalanced datasets

- New Models
- Random Oversampling and Undersampling
- Oversampling
- Class weights

Ensemble Learning

In [120…

```
X = dataset[dataset.columns.difference([target])]
Y = dataset[target]
```

In [121…

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, stratify = Y, random_state=1)
```

In [122…

```
trainSplitted = pd.concat([X_train, y_train], axis=1)
testSplitted = pd.concat([X_test, y_test], axis=1)
```

In [123…

```
def confusionMat(Y_test, y_pred,y_prob):
    cf_matrix = confusion_matrix(Y_test, y_pred)
    group_names = ['True Neg','False Pos','False Neg','True Pos']
    group_counts = ["{0:0.0f}".format(value) for value in
                cf_matrix.flatten()]
    group_percentages = ["{0:.2%}".format(value) for value in
                         cf_matrix.flatten()/np.sum(cf_matrix)]

    labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
          zip(group_names,group_counts,group_percentages)]
    labels = np.asarray(labels).reshape(2,2)
    fpr, tpr, thresh = roc_curve(Y_test, y_prob, pos_label=1)
    auc = roc_auc_score(Y_test, y_prob)
    fig, ax = plt.subplots(1, 2, figsize=(20, 8))
    sns.heatmap(cf_matrix, annot=labels, fmt="", cmap='Blues',ax=ax[0])
    plt.plot(fpr,tpr,label="AUC="+str(auc))
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.legend(loc=4)
    plt.show()
```

In [124…

```
def ROC_AUC(Y_test,y_pred):
    fpr, tpr, thresh = roc_curve(Y_test, y_pred, pos_label=1)
    plt.figure(figsize=(8,5))
    plt.plot(fpr,tpr)
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
```

1.AdaBoost

In [243…

```
clf = AdaBoostClassifier(n_estimators=50,random_state=0)
clf.fit(X_train, y_train)
```

Out[243…
```
AdaBoostClassifier(random_state=0)
```

In [244…
```
clf.score(X_train, y_train)
```

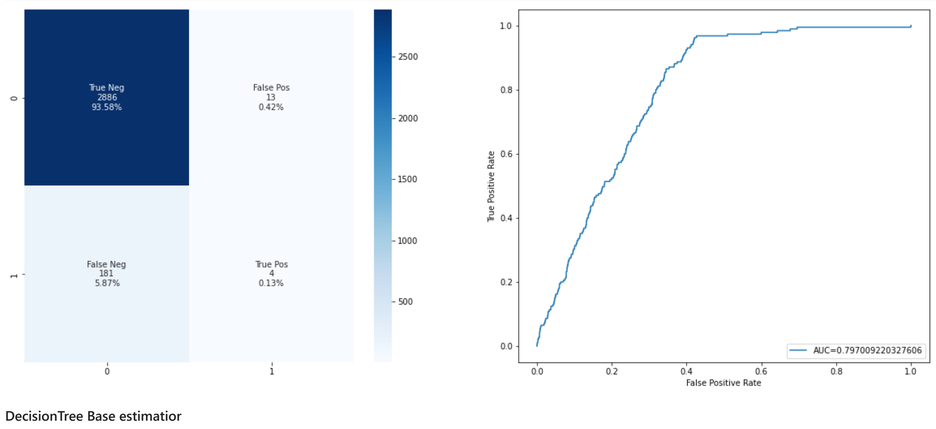
Out[244…
```
0.9364410214835833
```

In [245…
```
y_pred = clf.predict(X_test)
y_prob = clf.predict_proba(X_test)[:, 1]
```

In [246…
```
targetNames = ['Yes', 'No']
print('F1-Score : ' + str(f1_score(y_test, y_pred)))
print('Accuracy : ' + str(accuracy_score(y_test, y_pred)))
print()
print(classification_report(y_test, y_pred, target_names=targetNames))
```

```
F1-Score : 0.039603960396039604
Accuracy : 0.937094682230869

              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      2899
          No       0.24      0.02      0.04       185

    accuracy                           0.94      3084
   macro avg       0.59      0.51      0.50      3084
weighted avg       0.90      0.94      0.91      3084
```

In [249…
```
confusionMat(y_test, y_pred,y_prob)
```



DecisionTree Base estimatior

In [250…
```
DTC = DecisionTreeClassifier(random_state = 11, max_features = "auto")
ABC = AdaBoostClassifier(base_estimator = DTC)
```

In [251…
```
ABC.fit(X_train, y_train)
```

```
`base_estimator` was renamed to `estimator` in version 1.2 and will be removed in 1.4.
```

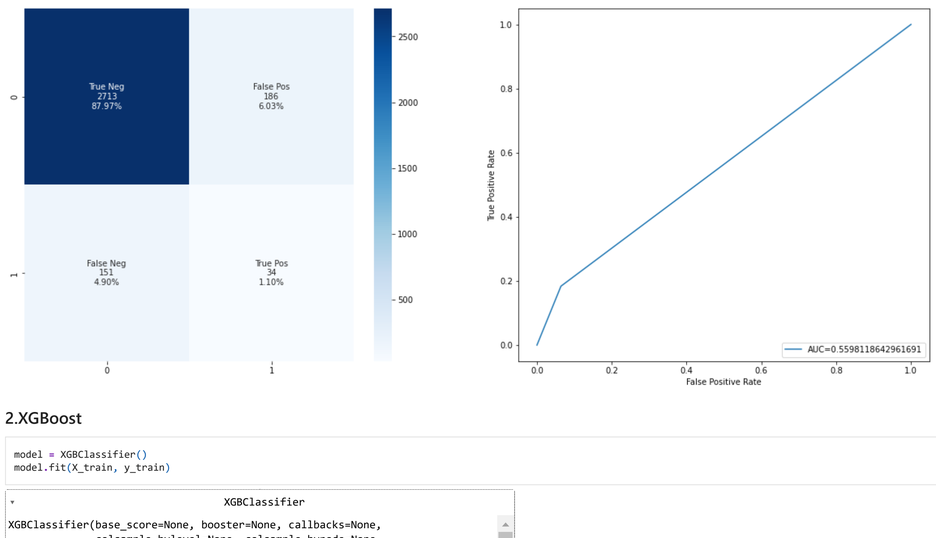
Out[251…
```
AdaBoostClassifier(base_estimator=DecisionTreeClassifier())
```

In [252…
```
y_pred = ABC.predict(X_test)
y_prob = ABC.predict_proba(X_test)[:, 1]
```

In [253…
```
targetNames = ['Yes', 'No']
print('F1-Score : ' + str(f1_score(y_test, y_pred)))
print('Accuracy : ' + str(accuracy_score(y_test, y_pred)))
print()
print(classification_report(y_test, y_pred, target_names=targetNames))
```

```
F1-Score : 0.16790123456790124
Accuracy : 0.8907263294422828

              precision    recall  f1-score   support

         Yes       0.95      0.94      0.94      2899
          No       0.15      0.18      0.17       185

    accuracy                           0.89      3084
   macro avg       0.55      0.56      0.55      3084
weighted avg       0.90      0.89      0.90      3084
```

In [254…
```
confusionMat(y_test, y_pred,y_prob)
```



2.XGBoost

In [255…
```
model = XGBClassifier()
model.fit(X_train, y_train)
```

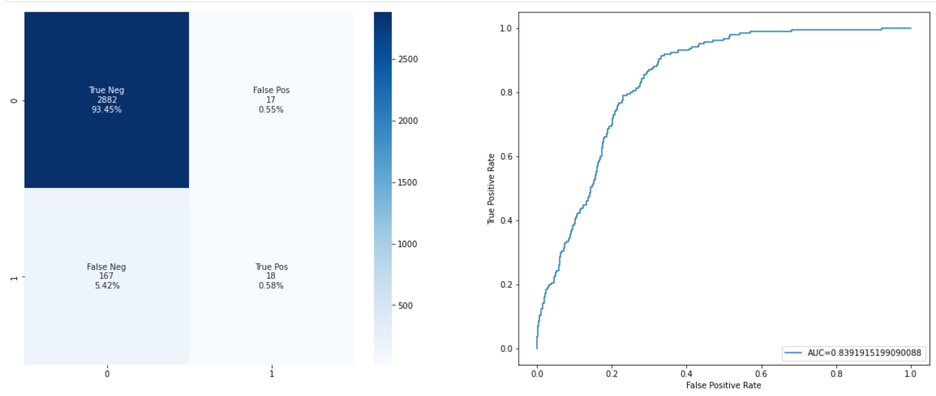
Out[255…
```
XGBClassifier(base_score=None, booster=None, callbacks=None,
              colsample_bylevel=None, colsample_bynode=None,
              colsample_bytree=None, early_stopping_rounds=None,
              enable_categorical=False, eval_metric=None, feature_types=None,
              gamma=None, gpu_id=None, grow_policy=None, importance_type=None,
              interaction_constraints=None, learning_rate=None, max_bin=None,
              max_cat_threshold=None, max_cat_to_onehot=None,
              max_delta_step=None, max_depth=None, max_leaves=None,
              min_child_weight=None, missing=nan, monotone_constraints=None,
              n_estimators=100, n_jobs=None, num_parallel_tree=None,
              predictor=None, random_state=None, ...)
```

In [256…
```
y_pred = model.predict(X_test)
y_prob = model.predict_proba(X_test)[:, 1]
```

In [257…
```
targetNames = ['Yes', 'No']
print('F1-Score : ' + str(f1_score(y_test, y_pred)))
print('Accuracy : ' + str(accuracy_score(y_test, y_pred)))
print()
print(classification_report(y_test, y_pred, target_names=targetNames))
```

```
F1-Score : 0.16363636363636364
Accuracy : 0.940337224383917

              precision    recall  f1-score   support

         Yes       0.95      0.99      0.97      2899
          No       0.51      0.10      0.16       185

    accuracy                           0.94      3084
   macro avg       0.73      0.55      0.57      3084
weighted avg       0.92      0.94      0.92      3084
```

In [258…
```
confusionMat(y_test, y_pred,y_prob)
```



Using grid search on it

In [259…
```
estimator = XGBClassifier(
    objective= 'binary:logistic',
    nthread=4,
    seed=42
)
```

In [260…
```
parameters = {
    'max_depth': range (2, 20, 1),
    'n_estimators': range(60, 300, 40),
    'learning_rate': [0.1, 0.01, 0.05]
}
```

In [261…
```
grid_search = GridSearchCV(
    estimator=estimator,
    param_grid=parameters,
    scoring = 'f1_micro',
    n_jobs = 10,
    cv = 5,
    verbose=True
)
```

In [ ]:
```
grid_search.fit(X_train, y_train)
```

```
Fitting 5 folds for each of 324 candidates, totalling 1620 fits
```

In [ ]:
```
y_pred = grid_search.predict(X_test)
y_prob = grid_search.predict_proba(X_test)[:, 1]
```

In [ ]:
```
targetNames = ['Yes', 'No']
print('F1-Score : ' + str(f1_score(y_test, y_pred)))
print('Accuracy : ' + str(accuracy_score(y_test, y_pred)))
print()
print(classification_report(y_test, y_pred, target_names=targetNames))
```

In [ ]:
```
confusionMat(y_test, y_pred,y_prob)
```

3.Gradient boosting

In [ ]:
```
gradientBoosting = GradientBoostingClassifier()
```

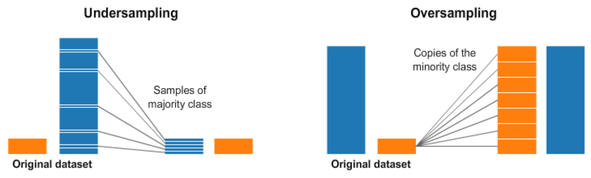
In [ ]:
```
gradientBoosting.fit(X_train, y_train)
```

In [ ]:
```
y_pred = gradientBoosting.predict(X_test)
y_prob = gradientBoosting.predict_proba(X_test)[:, 1]
```

In [ ]:
```
targetNames = ['Yes', 'No']
print('F1-Score : ' + str(f1_score(y_test, y_pred)))
print('Accuracy : ' + str(accuracy_score(y_test, y_pred)))
print()
print(classification_report(y_test, y_pred, target_names=targetNames))
```

In [ ]:
```
confusionMat(y_test, y_pred,y_prob)
```

Random Undersampling and Oversampling



- Models
- Models_stratifed
- Models_sampling
- Models_weighted

In [139…
```
class Models_Sampling():

    def __init__(self, train , test, target):
        self.target = target

        self.X_train= train[train.columns.difference([self.target])]
        self.X_test = test[test.columns.difference([self.target])]
        self.Y_train = train[self.target]
        self.Y_test = test[self.target]
        self.dictAccuracy = {}
        self.dictF1       = {}


    #Method for display confusion matrix and ROC a AUC
    def confusionMat(self, Y_test, y_pred,y_prob):
        cf_matrix = confusion_matrix(Y_test, y_pred)
        group_names = ['True Neg','False Pos','False Neg','True Pos']
        group_counts = ["{0:0.0f}".format(value) for value in
                        cf_matrix.flatten()]
        group_percentages = ["{0:.2%}".format(value) for value in
                             cf_matrix.flatten()/np.sum(cf_matrix)]

        labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
              zip(group_names,group_counts,group_percentages)]
        labels = np.asarray(labels).reshape(2,2)
        fpr, tpr, thresh = roc_curve(Y_test, y_prob, pos_label=1)
        auc = roc_auc_score(Y_test, y_prob)
        fig, ax = plt.subplots(1, 2, figsize=(20, 8))
        sns.heatmap(cf_matrix, annot=labels, fmt="", cmap='Blues',ax=ax[0])
        plt.plot(fpr,tpr,label="AUC="+str(auc))
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.legend(loc=4)

        plt.show()

    def Logistic(self):
        logreg = LogisticRegression(random_state=16, max_iter=1000)
        logreg.fit(self.X_train, self.Y_train)
        y_pred = logreg.predict(self.X_test)
        y_prob = logreg.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        print("\nLogisticRegression.....................................\n")
        print("Accuracy:", accuracy)
        self.dictAccuracy['LogisticRegression'] = accuracy
        print("F1-Score:", f1)
        self.dictF1['LogisticRegression'] = f1
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames,zero_division=1))



    #Decison Tree
    def DT(self,plt):
        dtc = DecisionTreeClassifier()
        dtc.fit(self.X_train, self.Y_train)
        y_pred = dtc.predict(self.X_test)
        y_prob = dtc.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['DecisionTree'] = accuracy
        self.dictF1['DecisionTree'] = f1
        print("\nDecisionTree.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))
        dtc.feature_importances_
        if plt:
            self.decisonFeature(self.dataset.columns.difference([target])
                                ,dtc.feature_importances_ )



    #Random forest
    def RF(self):
        rf = RandomForestClassifier(n_estimators=500, random_state=42)
        rf.fit(self.X_train, self.Y_train)
        y_pred = rf.predict(self.X_test)
        y_prob = rf.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['Random forest'] = accuracy
        self.dictF1['Random forest'] = f1
        print("\nRandomForest.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))

    #KNN
    def KNN(self):
        knn = KNeighborsClassifier()
        knn.fit(self.X_train, self.Y_train)
        y_pred = knn.predict(self.X_test)
        y_prob = knn.predict_proba(self.X_test)[:, 1]

        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['KNN'] = accuracy
        self.dictF1['KNN'] = f1
        print("\nKNN.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", str(f1))
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames))

    #SVC
    def SVC(self):
        clf = SVC(kernel='linear', probability=True)
        clf.fit(self.X_train,self.Y_train)
        y_pred = clf.predict(self.X_test)
        y_prob = clf.predict_proba(self.X_test)[:, 1]
        accuracy = accuracy_score(self.Y_test, y_pred)
        f1 = f1_score(self.Y_test, y_pred)
        self.dictAccuracy['SVC'] = accuracy
        self.dictF1['SVC'] = f1
        print("\nSVC.....................................\n")
        print("Accuracy:", accuracy)
        print("F1-Score:", f1)
        targetNames = ['Yes', 'No']
        self.confusionMat(self.Y_test, y_pred,y_prob)
        print(classification_report(self.Y_test, y_pred, target_names=targetNames , zero_division=1))

    #Metric Table
    def table(self):
        self.dictF1 = sorted(self.dictF1.items(), key=lambda x:x[1],reverse=True)
        self.dictAccuracy = sorted(self.dictAccuracy.items(), key=lambda x:x[1] ,reverse=True)
        acc = pd.DataFrame.from_dict(self.dictAccuracy)
        f1 = pd.DataFrame.from_dict(self.dictF1)

        print("\nF1-Score.....................................\n")
        print(f1)

        print("\nAccuracy.....................................\n")
        print(acc)

    #Feature importance
    def decisonFeature(self ,features ,importances ):
        print("\nFeature Importance.....................................\n")
        wid = len(features)
        print(len(features), len(importances))
        print(wid)
        figure(figsize=(20,wid))
        sorted_idx = importances.argsort()
        print(features[sorted_idx])
        plt.barh(features[sorted_idx], importances[sorted_idx])
        plt.show()


    def ROC_AUC(self,Y_test,y_pred):
        fpr, tpr, thresh = roc_curve(Y_test, y_pred, pos_label=1)
        plt.figure(figsize=(8,5))
        plt.plot(fpr,tpr)
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.show()
    #Output
    def testClassification(self):
        self.Logistic()
        self.DT(False)
        self.RF()
        self.KNN()
       # self.SVC()
        self.table()
```

In [126…
```
def getZeroOne(dataset):
    target =  'FraudFound_P'
    num0 = len(dataset[dataset[target]==0])
    num1 = len(dataset[dataset[target]==1])
    percent0 = (num0 / dataset.shape[0]) * 100
    percent1 = (num1 / dataset.shape[0]) * 100
    print("dataset shape   : " + str(dataset.shape))
    print("Number of zeros : " + str(num0) + " " + str(percent0) )
    print("Number of ones  : " + str(num1) + " " + str(percent1) )
```

In [127…
```
num_1 = len(dataset[dataset[target]==1])
num_0 = len(dataset[dataset[target]==0])
```

In [128…
```
dataset.shape[0]
```

Out[128…
```
15419
```

In [129…
```
getZeroOne(dataset)
```

```
dataset shape   : (15419, 76)
Number of zeros : 14496 94.01387898047862
Number of ones  : 923 5.98612101952137
```

In [130…
```
target =  'FraudFound_P'
```

In [131…
```
X = dataset[dataset.columns.difference([target])]
Y = dataset[target]
```

In [132…
```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, stratify = Y, random_state=1)
```

In [133…
```
trainSplitted = pd.concat([X_train, y_train], axis=1)
```

In [134…
```
testSplitted = pd.concat([X_test, y_test], axis=1)
```

In [135…
```
num_1 = len(trainSplitted[trainSplitted[target]==1])
num_0 = len(trainSplitted[trainSplitted[target]==0])
```

Random undersample

In [136…
```
undersampled_dataset = pd.concat([trainSplitted[trainSplitted[target]==0].sample(num_1) ,
                                  trainSplitted[trainSplitted[target]==1] ])
```

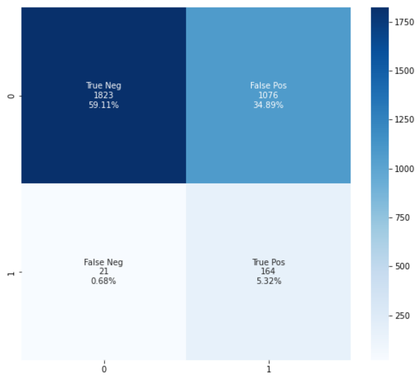
In [137…
```
getZeroOne(testSplitted)
```

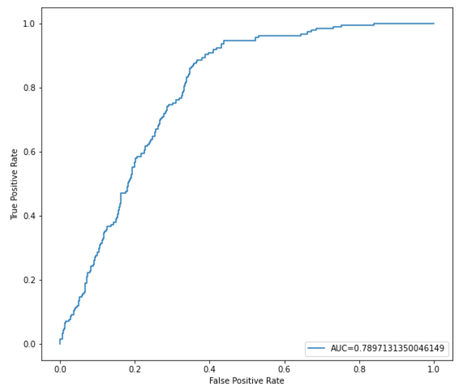
```
dataset shape   : (3084, 76)
Number of zeros : 2899 94.00129701686122
Number of ones  : 185 5.998702983138781
```

Test with stratified test

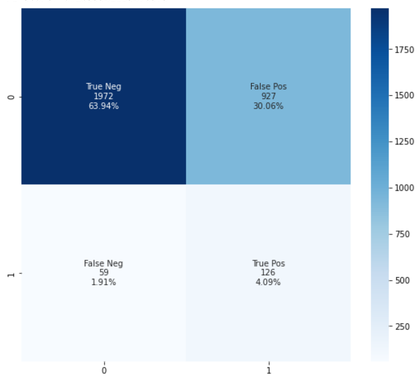
In [138…
```
modelFeatureAdding = Models_Sampling(undersampled_dataset,testSplitted,'FraudFound_P')
modelFeatureAdding.testClassification()
```

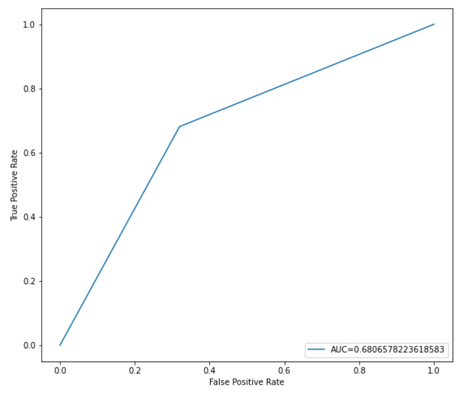
```
LogisticRegression.....................................

Accuracy: 0.6442931258106356
F1-Score: 0.23017543859649123
```



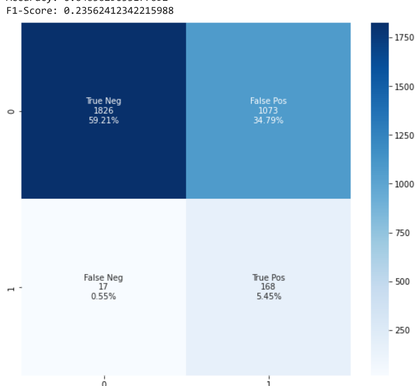


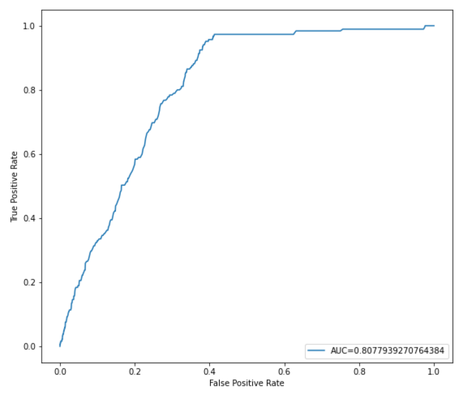

```
              precision    recall  f1-score   support

         Yes       0.99      0.63      0.77      2899
          No       0.13      0.89      0.23       185

    accuracy                           0.64      3084
   macro avg       0.56      0.76      0.50      3084
weighted avg       0.94      0.64      0.74      3084


DecisionTree.....................................

Accuracy: 0.6802853437094682
F1-Score: 0.2035541195476575
```



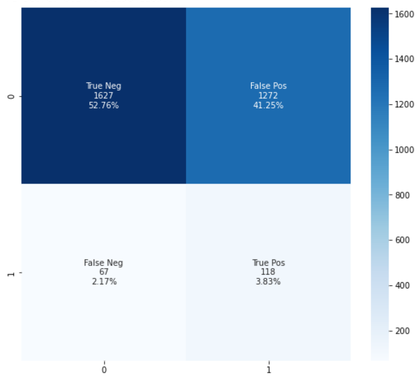


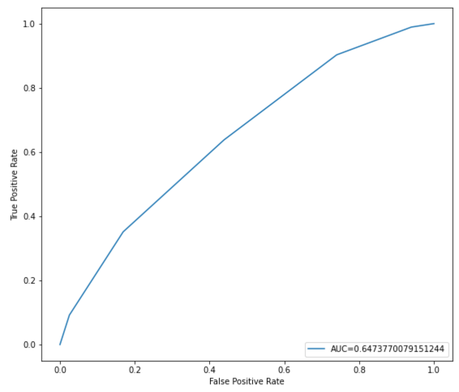

```
              precision    recall  f1-score   support

         Yes       0.97      0.68      0.80      2899
          No       0.12      0.68      0.20       185

    accuracy                           0.68      3084
   macro avg       0.55      0.68      0.50      3084
weighted avg       0.92      0.68      0.76      3084


RandomForest.....................................

Accuracy: 0.6465629053177692
F1-Score: 0.23562412342215988
```



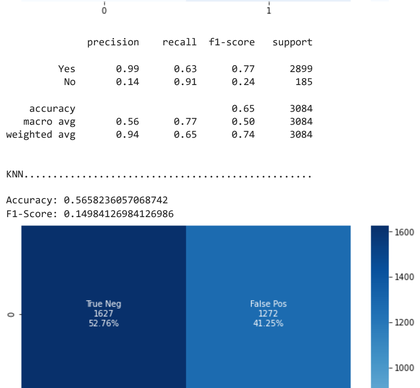


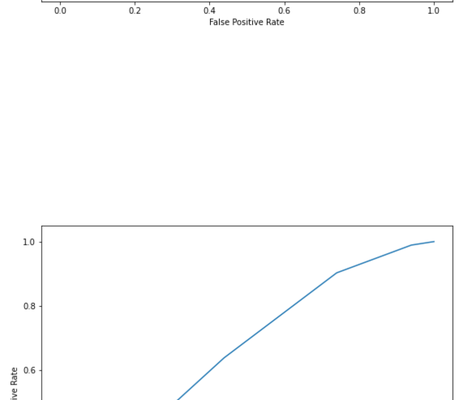

```
              precision    recall  f1-score   support

         Yes       0.99      0.63      0.77      2899
          No       0.14      0.91      0.24       185

    accuracy                           0.65      3084
   macro avg       0.56      0.77      0.50      3084
weighted avg       0.94      0.65      0.74      3084


KNN.....................................

Accuracy: 0.5658236057068742
F1-Score: 0.14984126984126986
```






```
              precision    recall  f1-score   support

         Yes       0.96      0.56      0.71      2899
          No       0.08      0.64      0.15       185

    accuracy                           0.57      3084
   macro avg       0.52      0.60      0.43      3084
weighted avg       0.91      0.57      0.67      3084


SVC.....................................

Accuracy: 0.6024643320363164
F1-Score: 0.21611253196930943
```





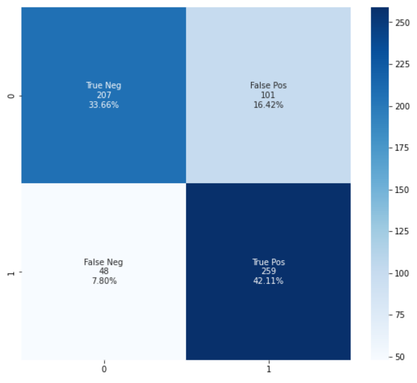

```
              precision    recall  f1-score   support

         Yes       0.99      0.58      0.73      2899
          No       0.12      0.91      0.22       185

    accuracy                           0.60      3084
   macro avg       0.56      0.75      0.47      3084
weighted avg       0.94      0.60      0.70      3084


F1-Score.....................................

                    0         1
0       Random forest  0.235624
1  LogisticRegression  0.230175
2                 SVC  0.216113
3        DecisionTree  0.203554
4                 KNN  0.149841

Accuracy.....................................

                    0         1
0        DecisionTree  0.680285
1       Random forest  0.646563
2  LogisticRegression  0.644293
3                 SVC  0.602464
4                 KNN  0.565824
```

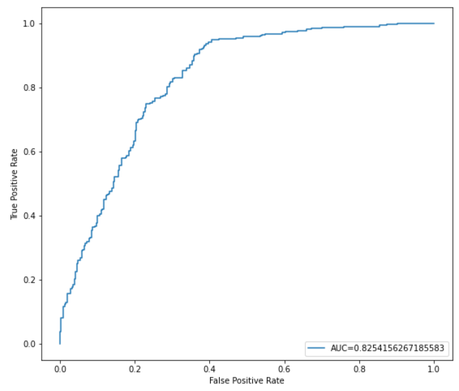
Test without stratified

In [139…
```
num_1 = len(dataset[dataset[target]==1])
undersample = pd.concat([dataset[dataset[target]==0].sample(num_1) ,
                         dataset[dataset[target]==1] ])
under = Models_Startified(undersample,'FraudFound_P',3)
under.testClassification()
```

```
LogisticRegression.....................................

List of possible accuracy: dict_values([0.7532467532467533, 0.7577235772357723, 0.734959349593496])
```

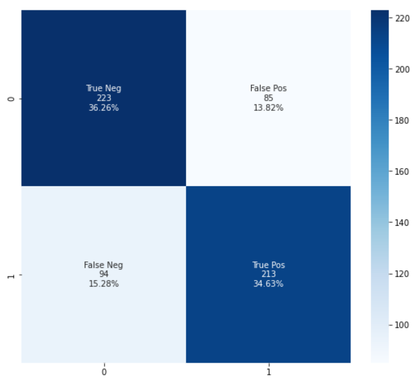
```
Maximum Accuracy That can be obtained from this model is: 75.77235772357723 %

Minimum Accuracy: 73.4959349593496 %

Overall Accuracy: 74.86432266920072 %

Standard Deviation is: 0.012060135056977353

List of possible F1-score: dict_values([0.7764705882352942, 0.7766116941529235, 0.7681365576102419])

Maximum F1-score That can be obtained from this model is: 77.66116941529235 %

Minimum F1-score: 76.8136557610242 %

Overall F1-score: 77.373961333282 %

Standard Deviation is: 0.0048529014818696785
```

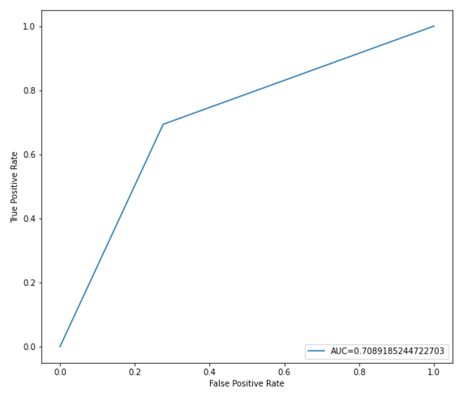




	precision	recall	f1-score	support
Yes	0.81	0.67	0.74	308
No	0.72	0.84	0.78	307
accuracy			0.76	615
macro avg	0.77	0.76	0.76	615
weighted avg	0.77	0.76	0.76	615

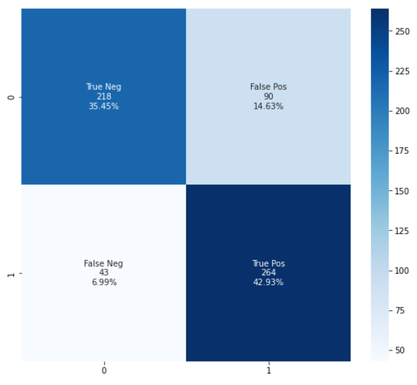
```
DecisionTree.....................................

List of possible accuracy: dict_values([0.6672077922077922, 0.7089430894308943, 0.6943089430894309])

Maximum Accuracy That can be obtained from this model is: 70.89430894308944 %

Minimum Accuracy: 66.72077922077922 %

Overall Accuracy: 69.01532749093725 %

Standard Deviation is: 0.021175715857846007

List of possible F1-score: dict_values([0.6611570247933884, 0.7041322314049586, 0.6977491961414791])

Maximum F1-score That can be obtained from this model is: 70.41322314049586 %

Minimum F1-score: 66.11570247933885 %

Overall F1-score: 68.76794841132754 %

Standard Deviation is: 0.023189791311587934
```

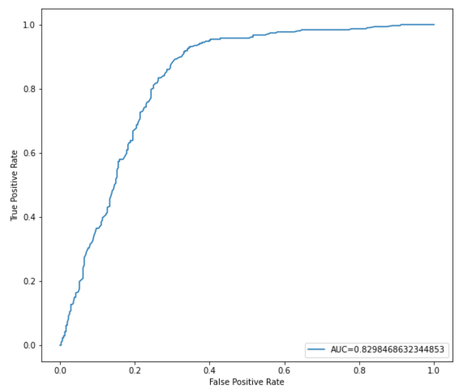




	precision	recall	f1-score	support
Yes	0.70	0.72	0.71	308
No	0.71	0.69	0.70	307
accuracy			0.71	615
macro avg	0.71	0.71	0.71	615
weighted avg	0.71	0.71	0.71	615

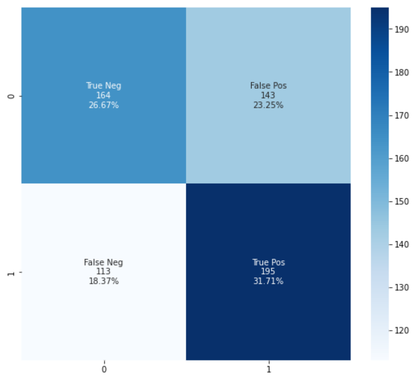
```
RandomForest.....................................

List of possible accuracy: dict_values([0.7629870129870129, 0.7837398373983739, 0.7609756097560976])

Maximum Accuracy That can be obtained from this model is: 78.3739837398374 %

Minimum Accuracy: 76.09756097560975 %

Overall Accuracy: 76.92341533804948 %

Standard Deviation is: 0.012602483380637693

List of possible F1-score: dict_values([0.7890173410404625, 0.7987897125567321, 0.7938288920056l])

Maximum F1-score That can be obtained from this model is: 79.87897125567322 %

Minimum F1-score: 78.90173410404626 %

Overall F1-score: 79.38786485342682 %

Standard Deviation is: 0.00488637575787082
```

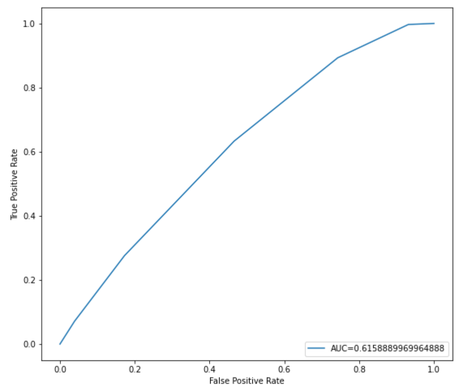




	precision	recall	f1-score	support
Yes	0.84	0.71	0.77	308
No	0.75	0.86	0.80	307
accuracy			0.78	615
macro avg	0.79	0.78	0.78	615
weighted avg	0.79	0.78	0.78	615

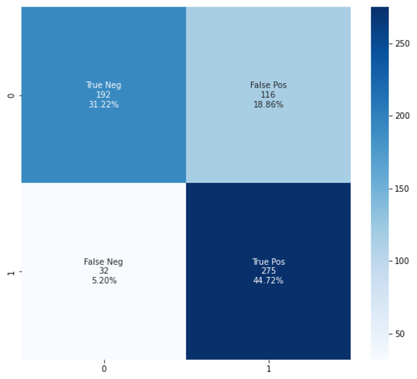
```
KNN.....................................

List of possible accuracy: dict_values([0.5422077922077922, 0.5577235772357724, 0.583739837398374])

Maximum Accuracy That can be obtained from this model is: 58.3739837398374 %

Minimum Accuracy: 54.22077922077923 %

Overall Accuracy: 56.12237356139795 %

Standard Deviation is: 0.020986091249504544

List of possible F1-score: dict_values([0.5422077922077922, 0.5641025641025642, 0.6037151702786377])

Maximum F1-score That can be obtained from this model is: 60.371517027863774 %

Minimum F1-score: 54.22077922077923 %

Overall F1-score: 57.0008508862998 %

Standard Deviation is: 0.03117610506337271
```

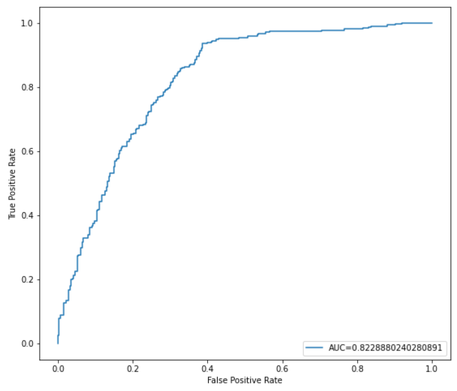




	precision	recall	f1-score	support
Yes	0.59	0.53	0.56	307
No	0.58	0.63	0.60	308
accuracy			0.58	615
macro avg	0.58	0.58	0.58	615
weighted avg	0.58	0.58	0.58	615

```
SVC.....................................

List of possible accuracy: dict_values([0.7467532467532467, 0.759349593495935, 0.7284552845528456])

Maximum Accuracy That can be obtained from this model is: 75.9349593495935 %

Minimum Accuracy: 72.84552845528455 %

Overall Accuracy: 74.48527082673424 %

Standard Deviation is: 0.015534594174617703

List of possible F1-score: dict_values([0.7808988764044943, 0.7879656160458453, 0.7690179806362379])

Maximum F1-score That can be obtained from this model is: 78.79656160458453 %

Minimum F1-score: 76.9017980636238 %

Overall F1-score: 77.92941576955258 %

Standard Deviation is: 0.009575205663850582
```






```
              precision    recall  f1-score   support

         Yes       0.86      0.62      0.72       308
          No       0.70      0.90      0.79       307

    accuracy                           0.76       615
   macro avg       0.78      0.76      0.75       615
weighted avg       0.78      0.76      0.75       615


F1-Score.....................................

                    0          1
0        RandomForest  79.878971
1                 SVC  78.796562
2  LogisticRegression  77.661169
3        DecisionTree  70.413223
4                 KNN  60.371517

Accuracy.....................................

                    0          1
0        RandomForest  78.373984
1                 SVC  75.934959
2  LogisticRegression  75.772358
3        DecisionTree  70.894309
4                 KNN  58.373984
```

Random Oversample

In [140…

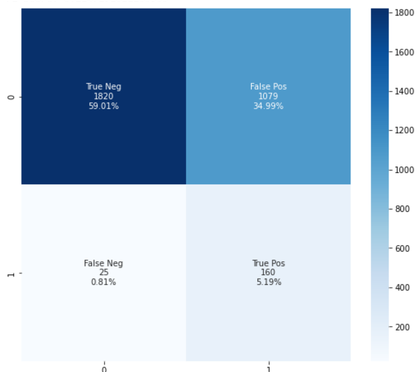
```
oversampled_dataset = pd.concat([trainSplitted[trainSplitted[target]==0] ,
                                 trainSplitted[trainSplitted[target]==1].sample(num_0, replace=True) ])
```

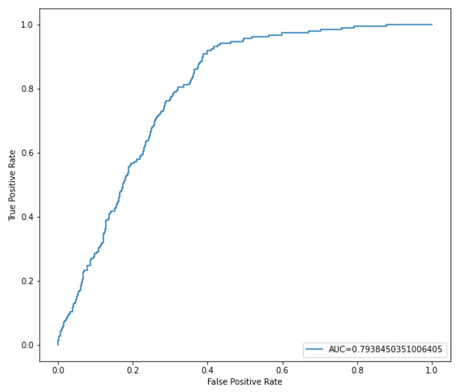
Stratified

In [141…

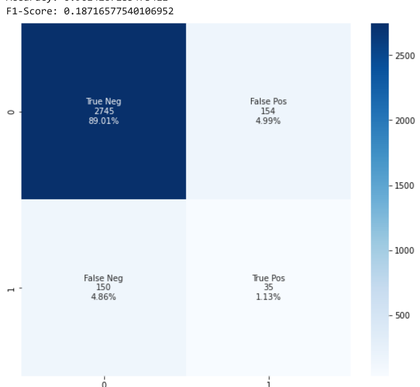
```
oversample = Models_Sampling(oversampled_dataset,testSplitted,'FraudFound_P')
oversample.testClassification()
```

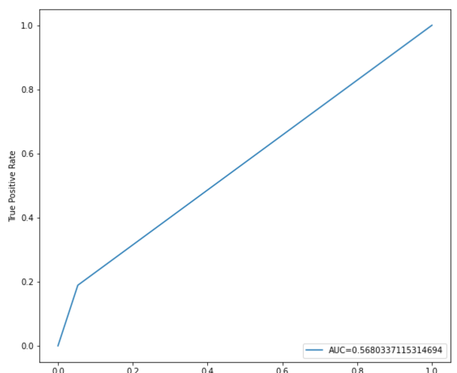
```
LogisticRegression.....................................

Accuracy: 0.642023346303502
F1-Score: 0.2247191011235955
```



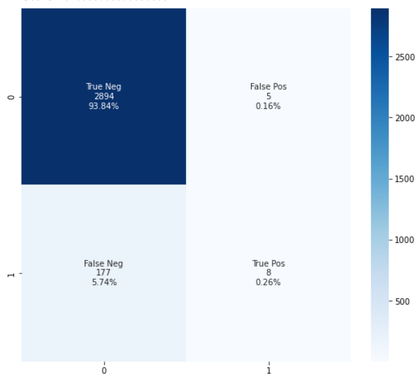


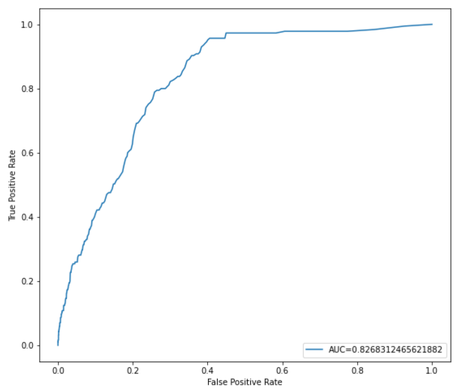

```
              precision    recall  f1-score   support

         Yes       0.99      0.63      0.77      2899
          No       0.13      0.86      0.22       185

    accuracy                           0.64      3084
   macro avg       0.56      0.75      0.50      3084
weighted avg       0.94      0.64      0.73      3084


DecisionTree.....................................

Accuracy: 0.9014267185473411
F1-Score: 0.18716577540106952
```



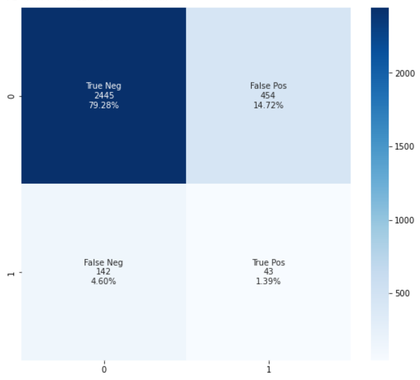


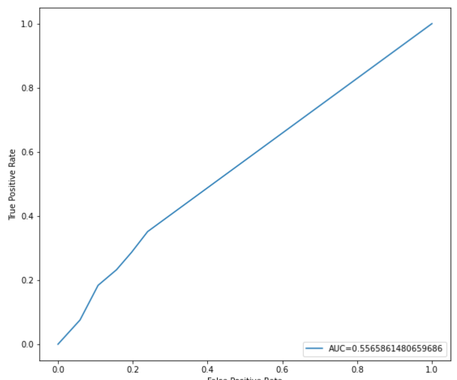

```
              precision    recall  f1-score   support

         Yes       0.95      0.95      0.95      2899
          No       0.19      0.19      0.19       185

    accuracy                           0.90      3084
   macro avg       0.57      0.57      0.57      3084
weighted avg       0.90      0.90      0.90      3084


RandomForest.....................................

Accuracy: 0.9409857328145266
F1-Score: 0.08080808080808081
```



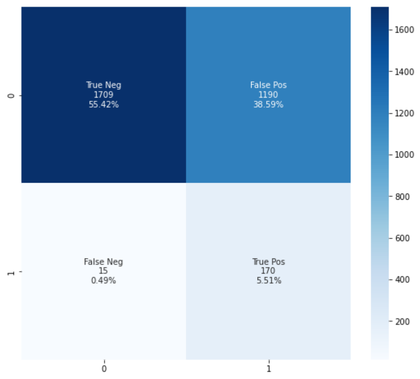


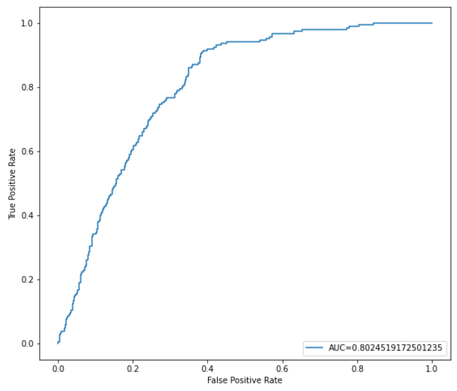

```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      2899
          No       0.62      0.04      0.08       185

    accuracy                           0.94      3084
   macro avg       0.78      0.52      0.53      3084
weighted avg       0.92      0.94      0.92      3084


KNN.....................................

Accuracy: 0.8067444876783398
F1-Score: 0.12609970674486803
```






```
              precision    recall  f1-score   support

         Yes       0.95      0.84      0.89      2899
          No       0.09      0.23      0.13       185

    accuracy                           0.81      3084
   macro avg       0.52      0.54      0.51      3084
weighted avg       0.89      0.81      0.85      3084


SVC.....................................

Accuracy: 0.6092736705577172
F1-Score: 0.2200647249190938
```



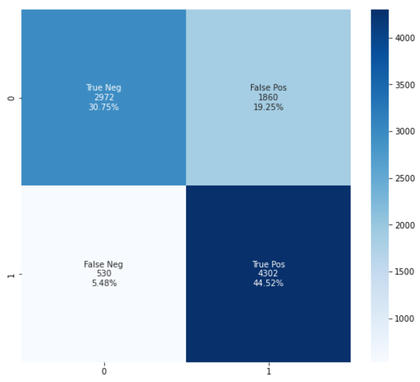


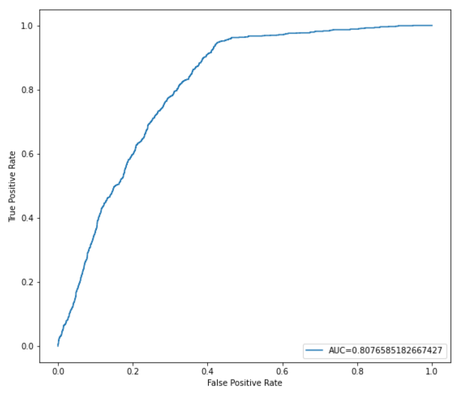

```
              precision    recall  f1-score   support

         Yes       0.99      0.59      0.74      2899
          No       0.12      0.92      0.22       185

    accuracy                           0.61      3084
   macro avg       0.56      0.75      0.48      3084
weighted avg       0.94      0.61      0.71      3084


F1-Score.....................................

                    0         1
0  LogisticRegression  0.224719
1                 SVC  0.220065
2        DecisionTree  0.187166
3                 KNN  0.126100
4       Random forest  0.080808

Accuracy.....................................

                    0         1
0       Random forest  0.940986
1        DecisionTree  0.901427
2                 KNN  0.806744
3  LogisticRegression  0.642023
4                 SVC  0.609274
```

Without stratified

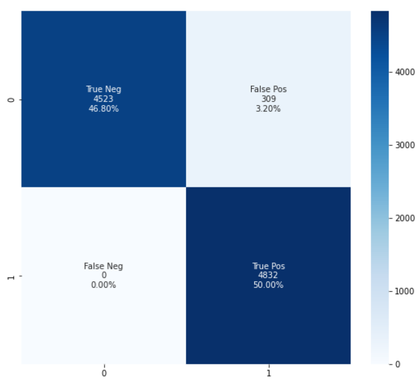
In [ ]:
```
num_1 = len(dataset[dataset[target]==1])
num_0 = len(dataset[dataset[target]==0])
overSample = pd.concat([dataset[dataset[target]==0] , dataset[dataset[target]==1].sample(num_0, replace=True) ])
over = Models_Startified(overSample,'FraudFound_P',3)
over.testClassification()
```

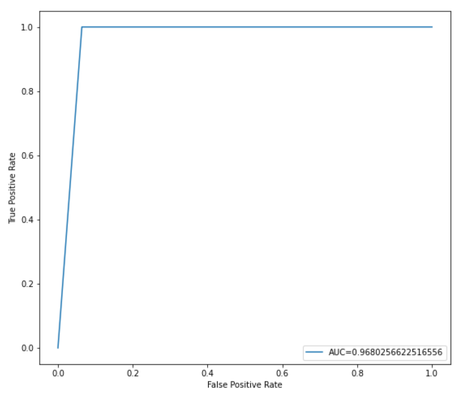
```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.................................

List of possible accuracy: dict_values([0.7526903973509934, 0.7510347682119205, 0.7469991721854304])

Maximum Accuracy That can be obtained from this model is: 75.26903973509934 %

Minimum Accuracy: 74.69991721854305 %

Overall Accuracy: 75.02414459161147 %

Standard Deviation is: 0.0029273761579358343

List of possible F1-score: dict_values([0.7826086956521738, 0.7805945650191501, 0.7782312925170067])

Maximum F1-score That can be obtained from this model is: 78.26086956521738 %

Minimum F1-score: 77.82312925170068 %

Overall F1-score: 78.04781843961102 %

Standard Deviation is: 0.0021910209695498264
```



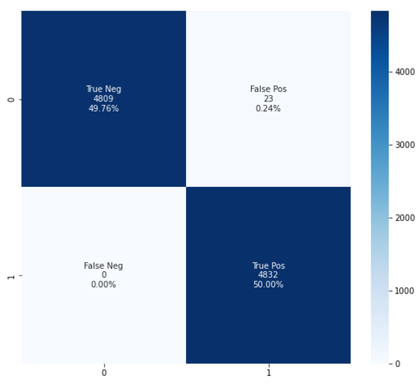


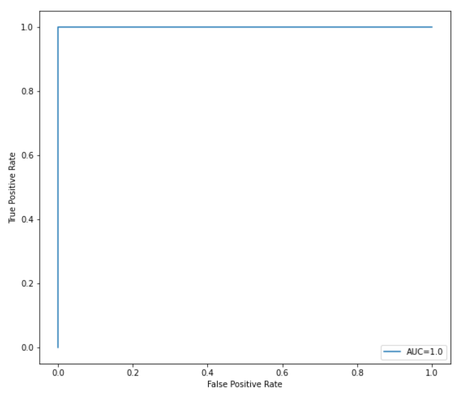

```
              precision    recall  f1-score   support

         Yes       0.85      0.62      0.71      4832
          No       0.70      0.89      0.78      4832

    accuracy                           0.75      9664
   macro avg       0.77      0.75      0.75      9664
weighted avg       0.77      0.75      0.75      9664


DecisionTree.....................................

List of possible accuracy: dict_values([0.9640935430463576, 0.9680256622516556, 0.9639900662251656])

Maximum Accuracy That can be obtained from this model is: 96.80256622516556 %

Minimum Accuracy: 96.39900662251655 %

Overall Accuracy: 96.5369757174393 %

Standard Deviation is: 0.0023006630995657125

List of possible F1-score: dict_values([0.965338128059135, 0.9690163441291488, 0.9651791074644788])

Maximum F1-score That can be obtained from this model is: 96.90163441291489 %

Minimum F1-score: 96.51791074644788 %

Overall F1-score: 96.65111932175876 %

Standard Deviation is: 0.00217098081627948
```





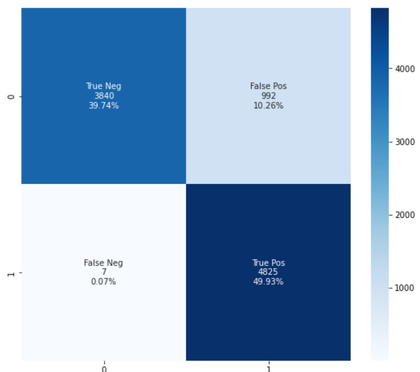

```
              precision    recall  f1-score   support

         Yes       1.00      0.94      0.97      4832
          No       0.94      1.00      0.97      4832

    accuracy                           0.97      9664
   macro avg       0.97      0.97      0.97      9664
weighted avg       0.97      0.97      0.97      9664


RandomForest.....................................

List of possible accuracy: dict_values([0.9965852649006622, 0.9976200331125827, 0.9955504966887417])

Maximum Accuracy That can be obtained from this model is: 99.76200331125827 %

Minimum Accuracy: 99.55504966887418 %

Overall Accuracy: 99.65852649006622 %

Standard Deviation is: 0.0010347682119205004

List of possible F1-score: dict_values([0.9965968856347325, 0.9976256839062662, 0.995570207067065])

Maximum F1-score That can be obtained from this model is: 99.76256839062661 %

Minimum F1-score: 99.5570207067065 %

Overall F1-score: 99.65975922026878 %

Standard Deviation is: 0.0010277386017620424
```

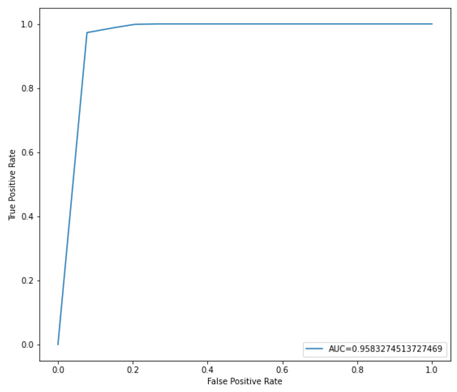





```
              precision    recall  f1-score   support

         Yes       1.00      1.00      1.00      4832
          No       1.00      1.00      1.00      4832

    accuracy                           1.00      9664
   macro avg       1.00      1.00      1.00      9664
weighted avg       1.00      1.00      1.00      9664


KNN.................................................

List of possible accuracy: dict_values([0.8930049668874173, 0.8966266556291391, 0.890521523178808])

Maximum Accuracy That can be obtained from this model is: 89.66266556291392 %

Minimum Accuracy: 89.0521523178808 %

Overall Accuracy: 89.33843818984548 %

Standard Deviation is: 0.0030701998912077587
```

```
List of possible F1-score: dict_values([0.902892561983471, 0.9061883744952578, 0.9011769101438446])

Maximum F1-score That can be obtained from this model is: 90.61883744952578 %

Minimum F1-score: 90.11769101438446 %

Overall F1-score: 90.34192822075244 %

Standard Deviation is: 0.0025469136974368644
```





	precision	recall	f1-score	support
Yes	1.00	0.79	0.88	4832
No	0.83	1.00	0.91	4832
accuracy			0.90	9664
macro avg	0.91	0.90	0.90	9664
weighted avg	0.91	0.90	0.90	9664

Oversampling using SMOTE

In [140…

```
smote = SMOTE(sampling_strategy='minority')
X_sm, y_sm = smote.fit_resample(X_train, y_train)
```

In [141…

```
smoteDataset_minority = pd.concat([X_sm, y_sm], axis=1, join="inner")
```

In [142…

```
getZeroOne(smoteDataset_minority)
```

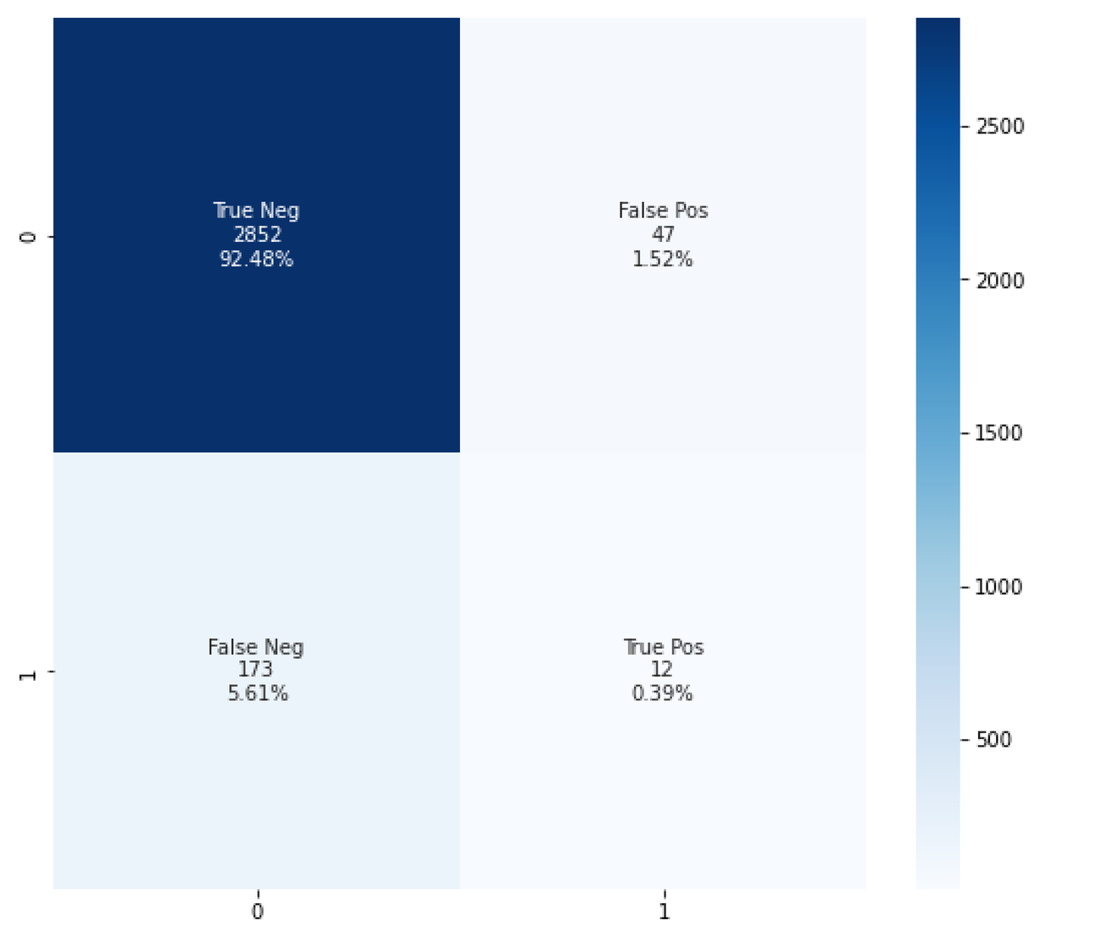
```
dataset shape   : (23194, 76)
Number of zeros : 11597 50.0
Number of ones  : 11597 50.0
```

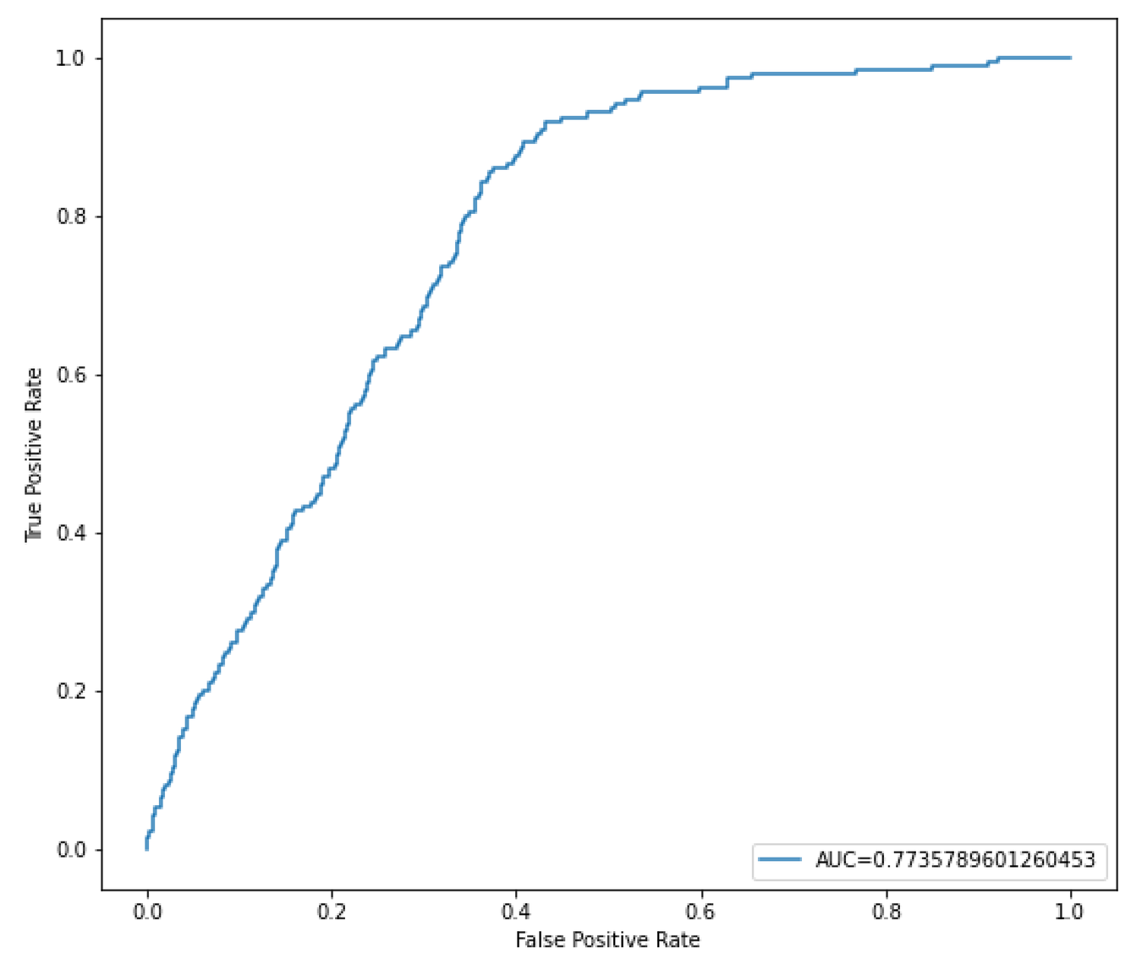
Test with stratified dataset

In [143…

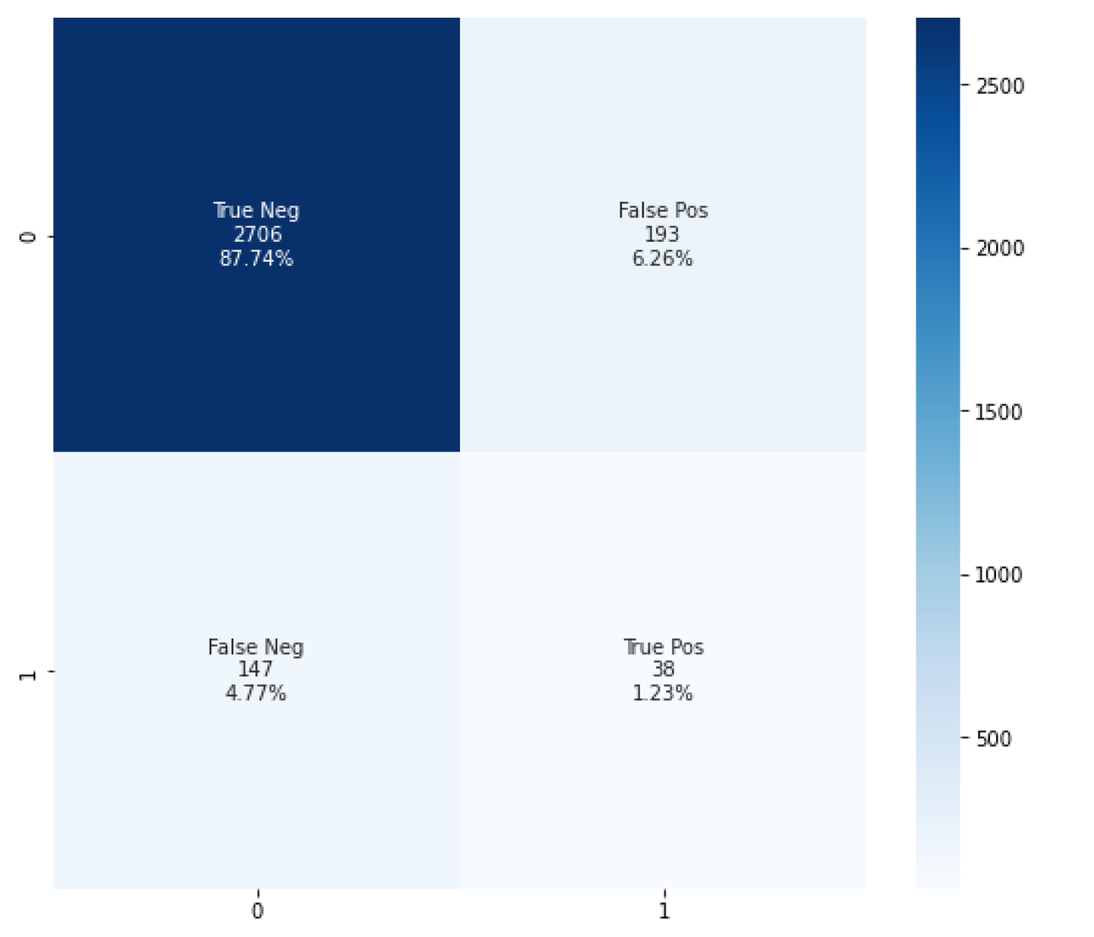
```
modelSmote= Models_Sampling(smoteDataset_minority,testSplitted,'FraudFound_P')
modelSmote.testClassification()
```

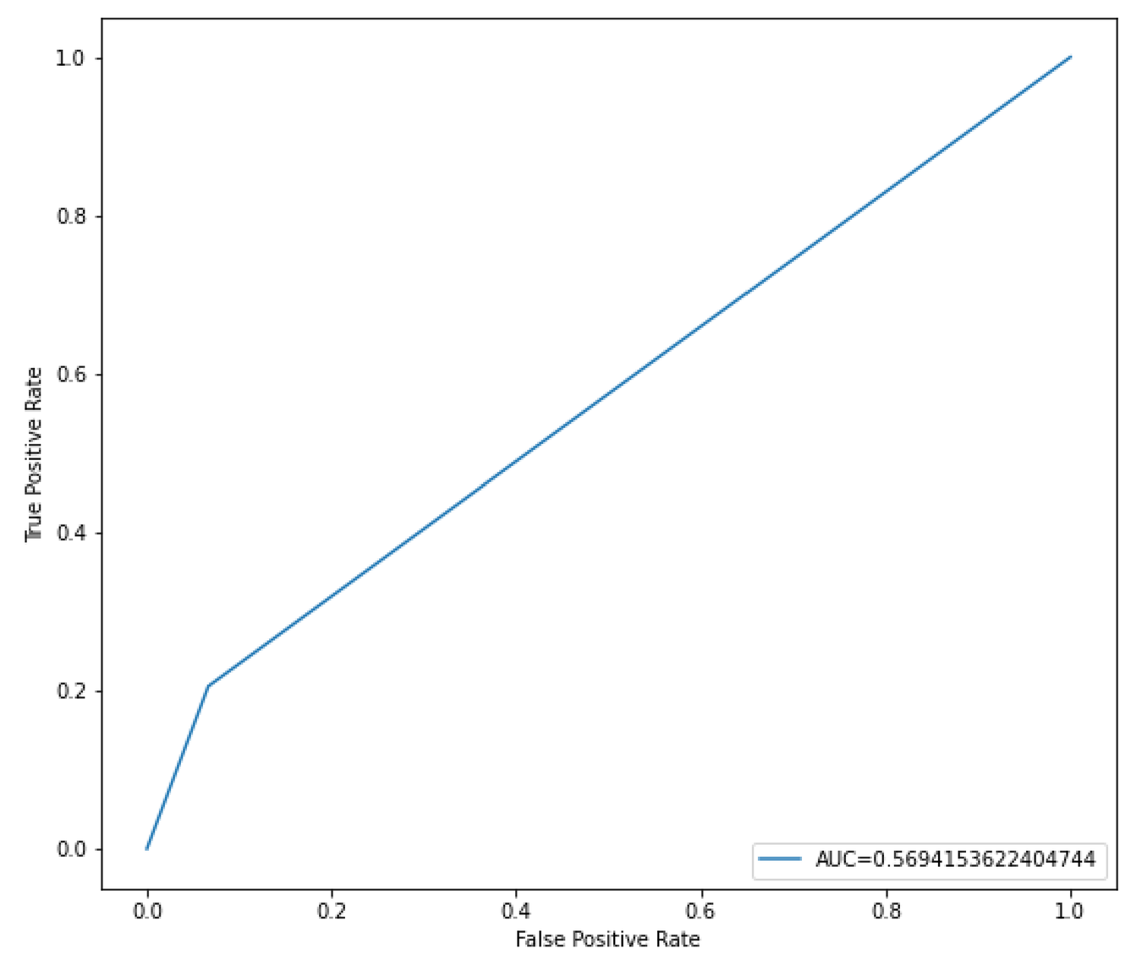
```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.................................

Accuracy: 0.9286640726329443
F1-Score: 0.09836065573770493
```



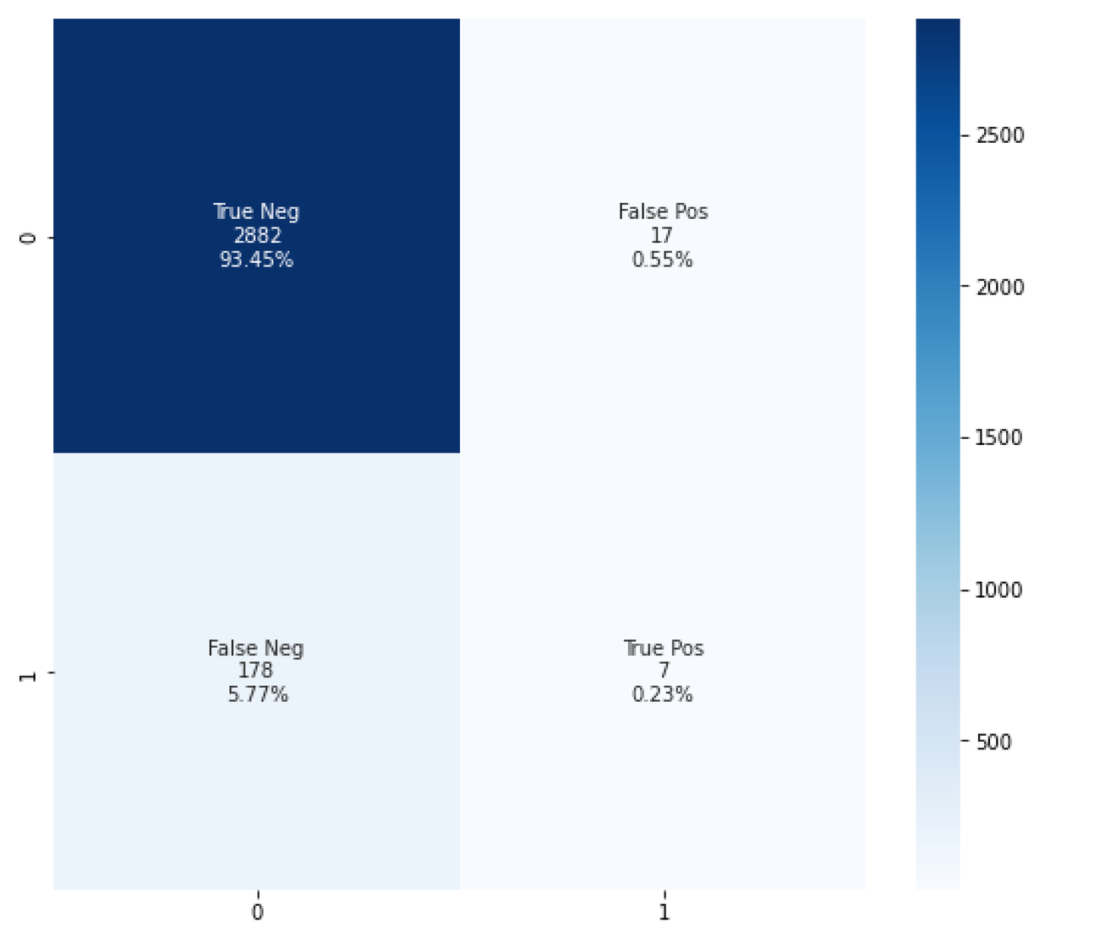


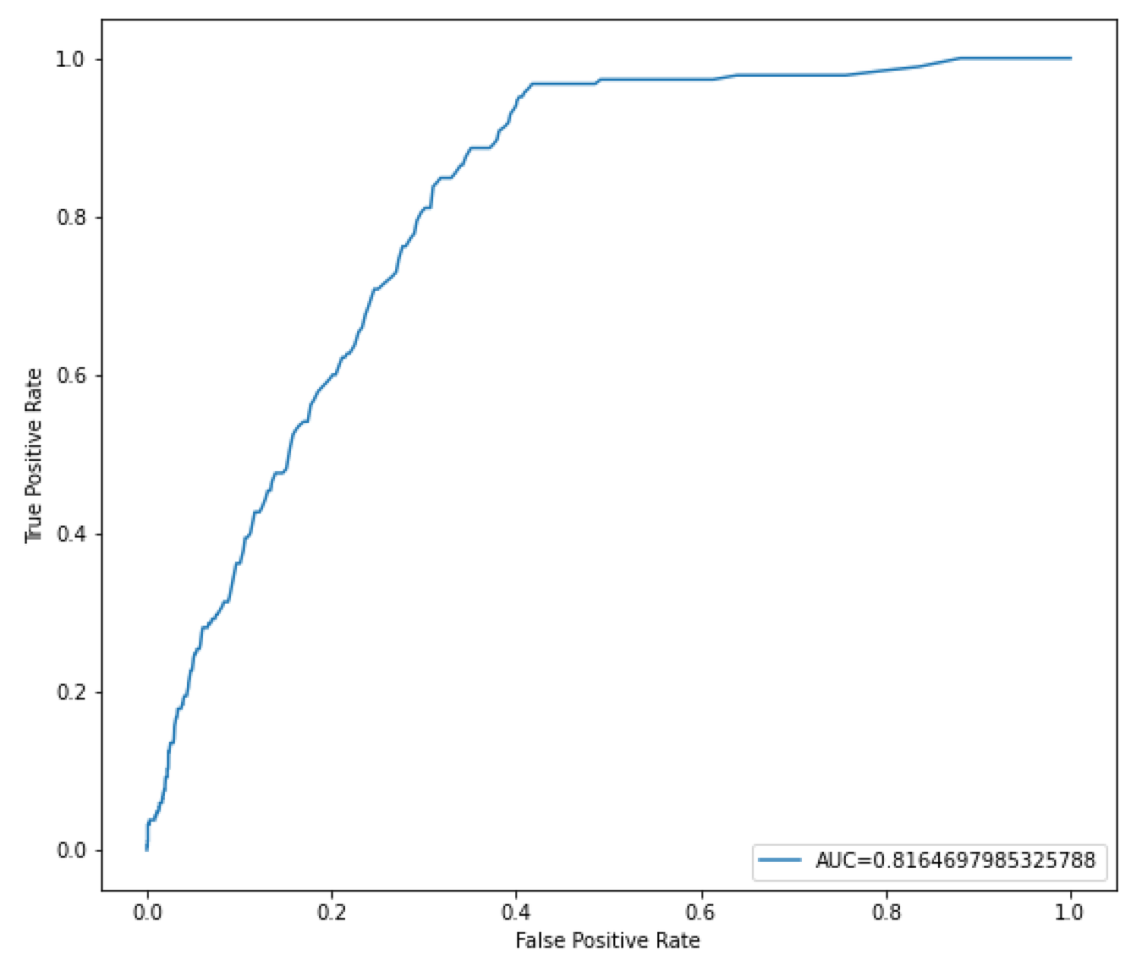

```
              precision    recall  f1-score   support

         Yes       0.94      0.98      0.96      2899
          No       0.20      0.06      0.10       185

    accuracy                           0.93      3084
   macro avg       0.57      0.52      0.53      3084
weighted avg       0.90      0.93      0.91      3084


DecisionTree.........................................

Accuracy: 0.8897535667963683
F1-Score: 0.18269230769230774
```



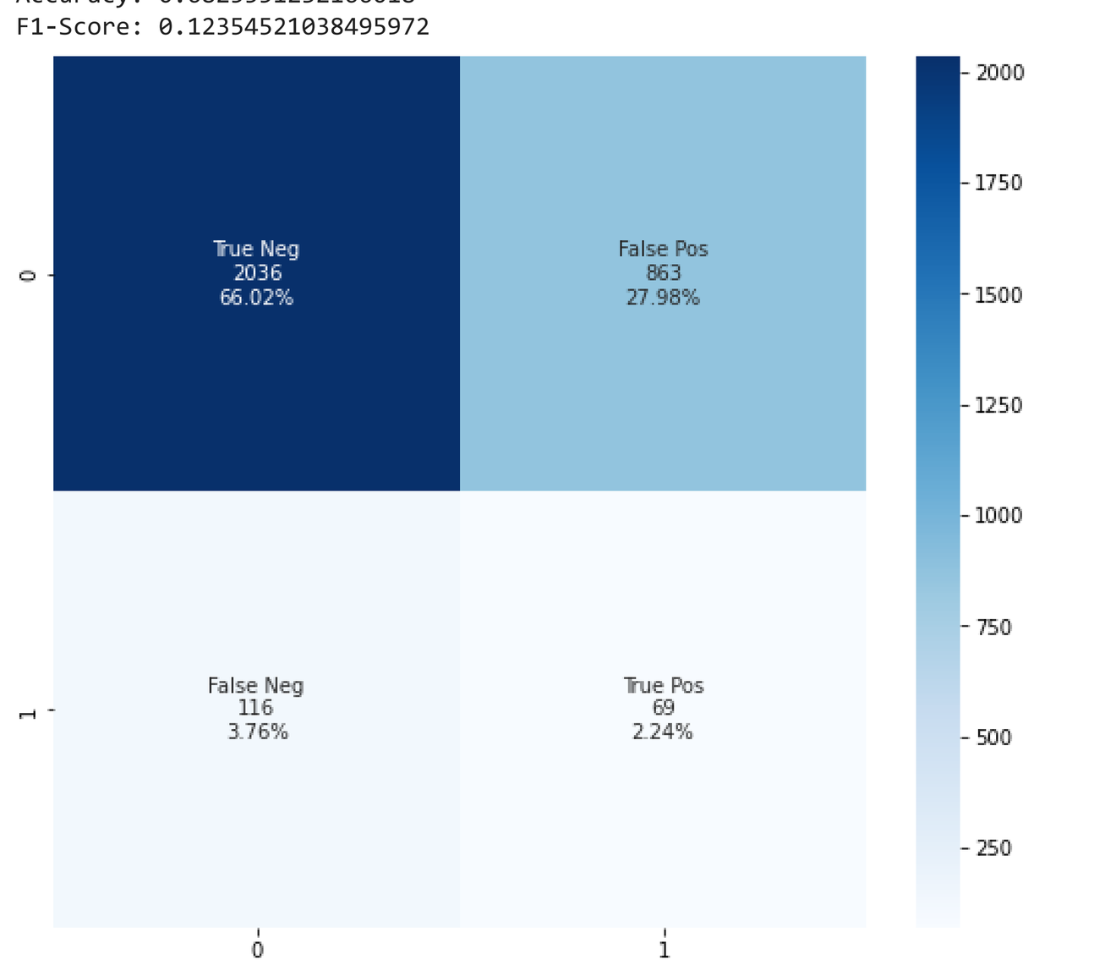


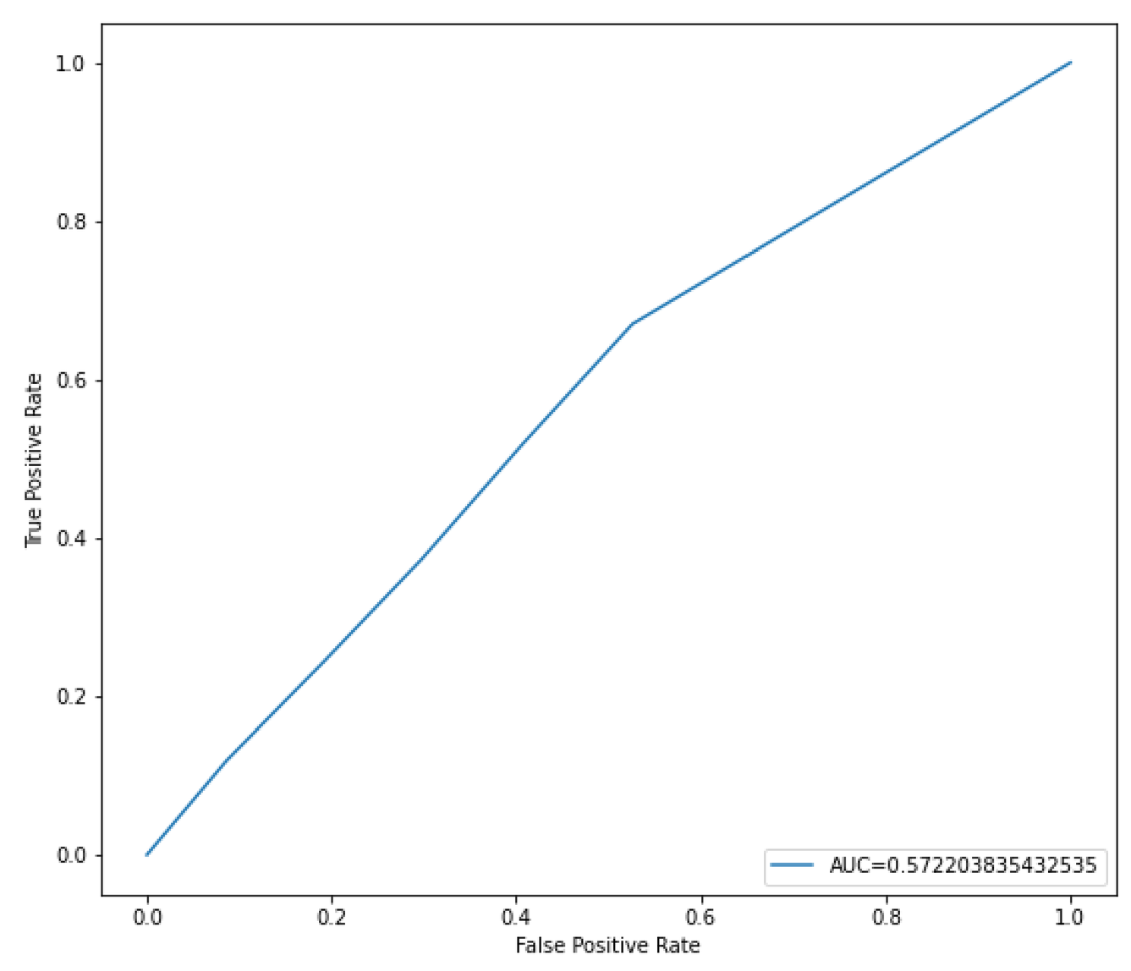

```
              precision    recall  f1-score   support

         Yes       0.95      0.93      0.94      2899
          No       0.16      0.21      0.18       185

    accuracy                           0.89      3084
   macro avg       0.56      0.57      0.56      3084
weighted avg       0.90      0.89      0.90      3084


RandomForest.........................................

Accuracy: 0.9367704280155642
F1-Score: 0.06698564593301436
```






```
              precision    recall  f1-score   support

         Yes       0.94      0.99      0.97      2899
          No       0.29      0.04      0.07       185

    accuracy                           0.94      3084
   macro avg       0.62      0.52      0.52      3084
weighted avg       0.90      0.94      0.91      3084


KNN..................................................

Accuracy: 0.6825551232166018
F1-Score: 0.12354521038495972
```





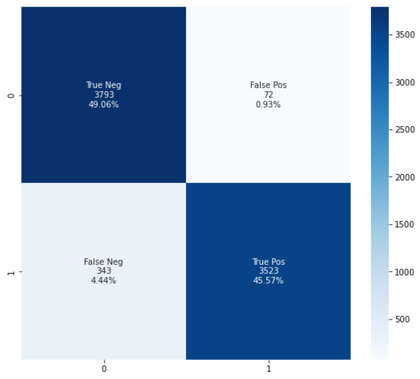

```
              precision    recall  f1-score   support

         Yes       0.95      0.70      0.81      2899
          No       0.07      0.37      0.12       185

    accuracy                           0.68      3084
   macro avg       0.51      0.54      0.46      3084
weighted avg       0.89      0.68      0.77      3084


F1-Score.............................................

                    0         1
0        DecisionTree  0.182692
1                 KNN  0.123545
2  LogisticRegression  0.098361
3       Random forest  0.066986

Accuracy.............................................

                    0         1
0       Random forest  0.936770
1  LogisticRegression  0.928664
2        DecisionTree  0.889754
3                 KNN  0.682555
```

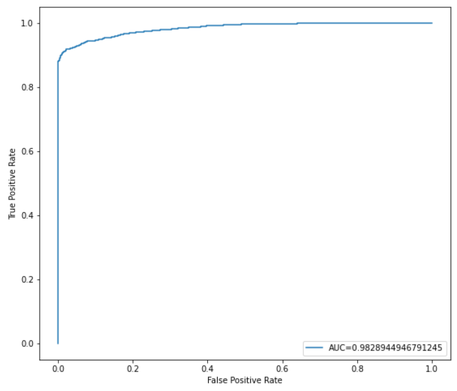
Test without stratified

In [144…

```python
smote = Models_Startified(smoteDataset_minority,'FraudFound_P',3)
smote.testClassification()
```

```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.................................

List of possible accuracy: dict_values([0.9458096223486808, 0.9403699392057948, 0.9463200103479498])

Maximum Accuracy That can be obtained from this model is: 94.63200103479498 %

Minimum Accuracy: 94.03699392057948 %

Overall Accuracy: 94.41665239674751 %

Standard Deviation is: 0.0032978274465042677

List of possible F1-score: dict_values([0.9436449226630801, 0.9378957294894247, 0.9443774292990216])

Maximum F1-score That can be obtained from this model is: 94.43774292990216 %

Minimum F1-score: 93.78957294894246 %

Overall F1-score: 94.19726938171755 %

Standard Deviation is: 0.003549700000033635
```





	precision	recall	f1-score	support
Yes	0.92	0.98	0.95	3865
No	0.98	0.91	0.94	3866
accuracy			0.95	7731
macro avg	0.95	0.95	0.95	7731
weighted avg	0.95	0.95	0.95	7731

DecisionTree.....................................

List of possible accuracy: dict_values([0.9355923435075013, 0.9340318199456733, 0.9326089768464623])

Maximum Accuracy That can be obtained from this model is: 93.55923435075013 %

Minimum Accuracy: 93.26089768464622 %

Overall Accuracy: 93.40777134332123 %

Standard Deviation is: 0.0014922127253507397

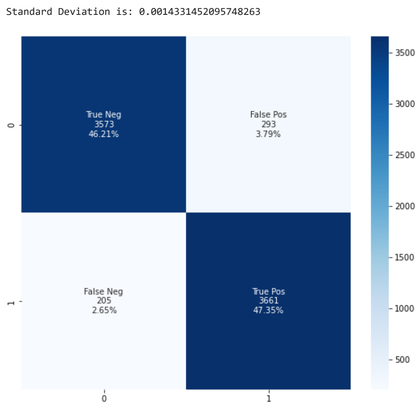
List of possible F1-score: dict_values([0.9363171355498722, 0.9347992840705703, 0.9334525482181634])

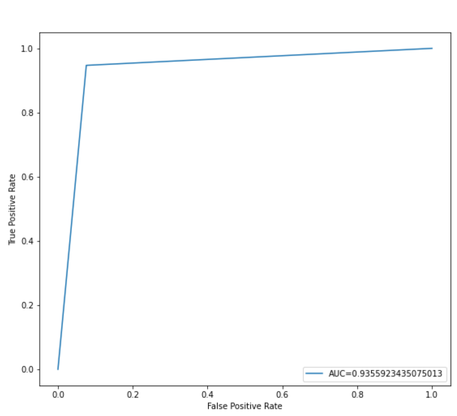
Maximum F1-score That can be obtained from this model is: 93.63171355498721 %

Minimum F1-score: 93.34525482181634 %

Overall F1-score: 93.48563226128687 %

Standard Deviation is: 0.0014331452095748263





	precision	recall	f1-score	support
Yes	0.95	0.92	0.93	3866
No	0.93	0.95	0.94	3866
accuracy			0.94	7732
macro avg	0.94	0.94	0.94	7732
weighted avg	0.94	0.94	0.94	7732

RandomForest.....................................

List of possible accuracy: dict_values([0.9711588204862908, 0.9699909455439141, 0.972577932997025])

Maximum Accuracy That can be obtained from this model is: 97.2577932997025 %

Minimum Accuracy: 96.9990945543914 %

Overall Accuracy: 97.124256634241 %

Standard Deviation is: 0.0012955253941745741

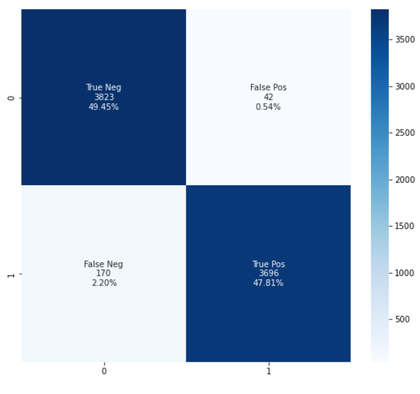
List of possible F1-score: dict_values([0.9707156927117532, 0.96932028563872, 0.9721199368753288])

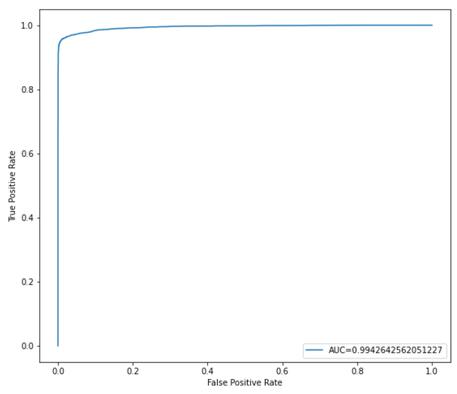
Maximum F1-score That can be obtained from this model is: 97.21199368753288 %

Minimum F1-score: 96.932028563872 %

Overall F1-score: 97.07186384086006 %

Standard Deviation is: 0.0013998279428232652





	precision	recall	f1-score	support
Yes	0.96	0.99	0.97	3865
No	0.99	0.96	0.97	3866
accuracy			0.97	7731
macro avg	0.97	0.97	0.97	7731
weighted avg	0.97	0.97	0.97	7731

KNN.....................................

List of possible accuracy: dict_values([0.8290222452146921, 0.840512223515716, 0.8425818134782046])

Maximum Accuracy That can be obtained from this model is: 84.25818134782045 %

Minimum Accuracy: 82.90222452146921 %

Overall Accuracy: 83.73720940695377 %

Standard Deviation is: 0.0073048465129173 69

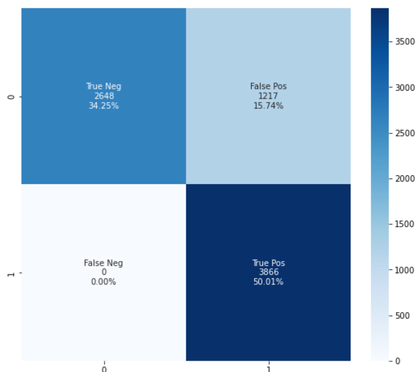
List of possible F1-score: dict_values([0.8539871879832117, 0.8624037495815199, 0.8640071516370544])

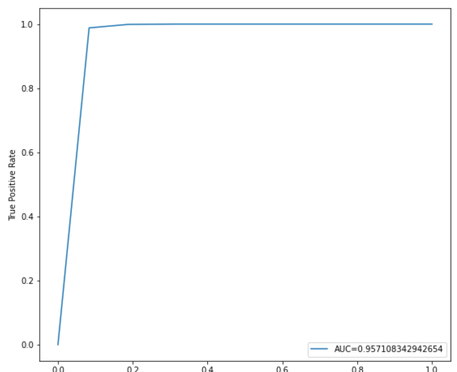
Maximum F1-score That can be obtained from this model is: 86.40071516370544 %

Minimum F1-score: 85.39871879832117 %

Overall F1-score: 86.01326964005953 %

Standard Deviation is: 0.0053822095666206556





	precision	recall	f1-score	support
Yes	1.00	0.69	0.81	3865
No	0.76	1.00	0.86	3866
accuracy			0.84	7731
macro avg	0.88	0.84	0.84	7731
weighted avg	0.88	0.84	0.84	7731

SVC.....................................

List of possible accuracy: dict_values([0.9416709777547853, 0.9367481567714396, 0.9416634329323503])

Maximum Accuracy That can be obtained from this model is: 94.16709777547852 %

Minimum Accuracy: 93.67481567714397 %

Overall Accuracy: 94.00275224861917 %

Standard Deviation is: 0.0028400165227345227

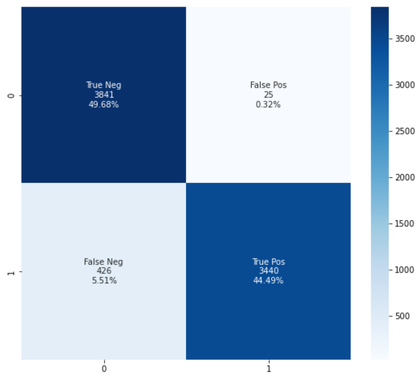
List of possible F1-score: dict_values([0.9384804255899605, 0.9328204423684572, 0.938362716960503])

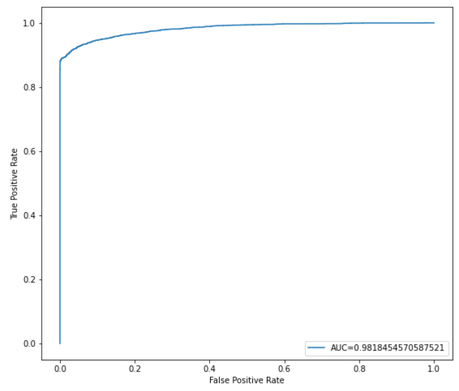
Maximum F1-score That can be obtained from this model is: 93.84804255899604 %

Minimum F1-score: 93.28204423684572 %

Overall F1-score: 93.6554528306307 %

Standard Deviation is: 0.003234348802123445






```
              precision    recall  f1-score   support

         Yes       0.90      0.99      0.94      3866
          No       0.99      0.89      0.94      3866

    accuracy                           0.94      7732
   macro avg       0.95      0.94      0.94      7732
weighted avg       0.95      0.94      0.94      7732


F1-Score.....................................

                    0          1
0        RandomForest  97.211994
1  LogisticRegression  94.437743
2                 SVC  93.848043
3        DecisionTree  93.631714
4                 KNN  86.400715

Accuracy.....................................

                    0          1
0        RandomForest  97.257793
1  LogisticRegression  94.632001
2                 SVC  94.167098
3        DecisionTree  93.559234
4                 KNN  84.258181
```

- Models
- Models_stratifed
- Models_sampling
- Models_weighted

Class weights in the models

In [145…

```
class Models_Startified_WeightClass():

    def __init__(self, dataset, target,Ksplit,zero,one):
        self.zero = zero
        self.one = one
        self.Ksplit = Ksplit
        self.dataset = dataset
        self.target = target
        self.X = self.dataset[dataset.columns.difference([self.target])]
        self.Y = self.dataset[self.target]
        self.X_train, self.X_test, self.Y_train, self.Y_test = train_test_split(self.X, self.Y,
                                                                                 test_size = 1/5, random_state = 0 )
        self.dictAccuracy = {}
        self.dictF1       = {}
        self.skf = StratifiedKFold(n_splits=self.Ksplit, shuffle=True, random_state=1)




    def confusionMat(self, Y_test, y_pred,y_prob):
        cf_matrix = confusion_matrix(Y_test, y_pred)
        group_names = ['True Neg','False Pos','False Neg','True Pos']
        group_counts = ["{0:0.0f}".format(value) for value in
                        cf_matrix.flatten()]
        group_percentages = ["{0:.2%}".format(value) for value in
                             cf_matrix.flatten()/np.sum(cf_matrix)]

        labels = [f"{v1}\n{v2}\n{v3}" for v1, v2, v3 in
                  zip(group_names,group_counts,group_percentages)]
        labels = np.asarray(labels).reshape(2,2)
        fpr, tpr, thresh = roc_curve(Y_test, y_prob, pos_label=1)
        auc = roc_auc_score(Y_test, y_prob)
        fig, ax = plt.subplots(1, 2, figsize=(20, 8))
        sns.heatmap(cf_matrix, annot=labels, fmt="", cmap='Blues',ax=ax[0])
        plt.plot(fpr,tpr,label="AUC="+str(auc))
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.legend(loc=4)
        plt.show()


    def possibility_acc_f1(self,dictAcc,dictF1):
        print('List of possible accuracy:', dictAcc.values())
        print('\nMaximum Accuracy That can be obtained from this model is:',
              max(dictAcc.values())*100, '%')
        print('\nMinimum Accuracy:',
              min(dictAcc.values())*100, '%')
        print('\nOverall Accuracy:',
              mean(dictAcc.values())*100, '%')
        print('\nStandard Deviation is:', stdev(dictAcc.values()))
        print()
        print('List of possible F1-score:', dictF1.values())
        print('\nMaximum F1-score That can be obtained from this model is:',
              max(dictF1.values())*100, '%')
        print('\nMinimum F1-score:',
              min(dictF1.values())*100, '%')
        print('\nOverall F1-score:',
              mean(dictF1.values())*100, '%')
        print('\nStandard Deviation is:', stdev(dictF1.values()))
        print()


    #Logistic
    def Logistic(self):
        #Define dictionaries for possible folds
        log_accu_stratified = {}
        log_f1_stratified = {}
        Y_pred ={}
        Y_test ={}
        Y_prob = {}

        #Define Model
        logreg = LogisticRegression(random_state=16, max_iter=1000,class_weight={0:self.zero,1:self.one})
        n = 0
        for train_index, test_index in self.skf.split(self.X ,self.Y):
            n=n+1
            x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
            y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
            Y_test[n] = y_test_fold

            logreg.fit(x_train_fold, y_train_fold)
            y_prediction = logreg.predict(x_test_fold)
            y_prob = logreg.predict_proba(x_test_fold)[:, 1]

            log_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
            log_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
            Y_pred[n] = y_prediction
            Y_prob[n] =  y_prob

        print("\nLogisticRegression.................................\n")
        self.possibility_acc_f1(log_accu_stratified,log_f1_stratified)

        self.dictAccuracy['LogisticRegression'] =  max(log_accu_stratified.values())*100
        self.dictF1['LogisticRegression'] = max(log_f1_stratified.values())*100
        targetNames = ['Yes', 'No']
        #print confusion matrix and AUC-ROC for maximum F1-score
        max_n = max(log_f1_stratified, key=lambda x:log_f1_stratified[x])
        self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
        print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))



    #Decison Tree
    def DT(self,plt):
        #Define dictionaries for possible folds
        dt_accu_stratified = {}
        dt_f1_stratified = {}
        Y_pred ={}
        Y_prob = {}
        feat_importance={}
        Y_test ={}
        #Define Model
        dtc = DecisionTreeClassifier(class_weight={0:self.zero,1:self.one})
        #Fold counter
        n = 0
        for train_index, test_index in self.skf.split(self.X ,self.Y):
            n=n+1
            x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
            y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
            Y_test[n] = y_test_fold
            dtc.fit(x_train_fold, y_train_fold)
            y_prediction = dtc.predict(x_test_fold)
            y_prob = dtc.predict_proba(x_test_fold)[:, 1]

            dt_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
            dt_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
            Y_pred[n] = y_prediction
            Y_prob[n] = y_prob

            feat_importance[n]= dtc.feature_importances_

        print("\nDecisionTree.....................................\n")
        self.possibility_acc_f1(dt_accu_stratified,dt_f1_stratified)
        self.dictAccuracy['DecisionTree'] =  max(dt_accu_stratified.values())*100
        self.dictF1['DecisionTree'] = max(dt_f1_stratified.values())*100
        targetNames = ['Yes', 'No']
        #print confusion matrix and AUC-ROC for maximum F1-score
        max_n = max(dt_f1_stratified, key=lambda x:dt_f1_stratified[x])
        self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
        print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))
        if plt:
            self.decisonFeature(self.dataset.columns.difference([target])
                                ,feat_importance[max_n])



    #Random forest
    def RF(self):
        #Define dictionaries for possible folds
        rf_accu_stratified = {}
        rf_f1_stratified = {}
        Y_pred ={}
        Y_test = {}
        Y_prob = {}

        #Define Model
        rf = RandomForestClassifier(n_estimators=500, random_state=42,class_weight={0:self.zero,1:self.one})
        #Fold counter
        n = 0
        for train_index, test_index in self.skf.split(self.X ,self.Y):
            n=n+1
            x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
            y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
            Y_test[n]=y_test_fold
            rf.fit(x_train_fold, y_train_fold)
            y_prediction = rf.predict(x_test_fold)
            y_prob = rf.predict_proba(x_test_fold)[:, 1]

            rf_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
            rf_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
            Y_pred[n] = y_prediction
            Y_prob[n] =  y_prob

        print("\nRandomForest.....................................\n")
        self.possibility_acc_f1(rf_accu_stratified,rf_f1_stratified)
        self.dictAccuracy['RandomForest'] =  max(rf_accu_stratified.values())*100
        self.dictF1['RandomForest'] = max(rf_f1_stratified.values())*100
        targetNames = ['Yes', 'No']
        #print confusion matrix and AUC-ROC for maximum F1-score
        max_n = max(rf_f1_stratified, key=lambda x:rf_f1_stratified[x])
        self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
        print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))



    #SVC
    def SVC(self,kernel):
        #Define dictionaries for possible folds
        svc_accu_stratified = {}
        svc_f1_stratified = {}
        Y_pred ={}
        Y_test={}
        Y_prob = {}
        #Define Model
        clf = SVC(kernel=kernel,class_weight={0:self.zero,1:self.one})
        #Fold counter
        n = 0
        for train_index, test_index in self.skf.split(self.X ,self.Y):
            n=n+1
            x_train_fold, x_test_fold = self.X.values[train_index], self.X.values[test_index]
            y_train_fold, y_test_fold = self.Y.values[train_index],self.Y.values[test_index]
            Y_test[n]=y_test_fold
```

```
            clf.fit(x_train_fold, y_train_fold)
            y_prediction = clf.predict(x_test_fold)
            y_prob = clf.predict_proba(x_test_fold)[:, 1]
            svc_accu_stratified[n] = accuracy_score(y_test_fold ,y_prediction)
            svc_f1_stratified[n]   = f1_score(y_test_fold,y_prediction)
            Y_pred[n] = y_prediction
            Y_prob[n] = y_prob

        print("\nSVC.....................................................\n")
        self.possibility_acc_f1(svc_accu_stratified,svc_f1_stratified)
        self.dictAccuracy['SVC'] =  max(svc_accu_stratified.values())*100
        self.dictF1['SVC'] = max(svc_f1_stratified.values())*100
        targetNames = ['Yes', 'No']
        #print confusion matrix and AUC-ROC for maximum F1-score
        max_n = max(svc_f1_stratified, key=lambda x:svc_f1_stratified[x])
        self.confusionMat(Y_test[max_n], Y_pred[max_n],Y_prob[max_n])
        print(classification_report(Y_test[max_n], Y_pred[max_n], target_names=targetNames,zero_division=1))

    #Metric Table
    def table(self):
        self.dictF1 = sorted(self.dictF1.items(), key=lambda x:x[1],reverse=True)
        self.dictAccuracy = sorted(self.dictAccuracy.items(), key=lambda x:x[1] ,reverse=True)
        acc = pd.DataFrame.from_dict(self.dictAccuracy)
        f1 = pd.DataFrame.from_dict(self.dictF1)

        print("\nF1-Score.....................................\n")
        print(f1)

        print("\nAccuracy.....................................\n")
        print(acc)

    #Feature importance
    def decisonFeature(self ,features ,importances ):
        print("\nFeature Importance.....................\n")
        wid = len(features)
        print(wid)
        figure(figsize=(20, wid*2))
        sorted_idx = importances.argsort()
        plt.barh(features[sorted_idx], importances[sorted_idx])
        plt.show()


    def ROC_AUC(self,Y_test,y_pred):
        fpr, tpr, thresh = roc_curve(Y_test, y_pred, pos_label=1)
        plt.figure(figsize=(8,5))
        plt.plot(fpr,tpr)
        plt.ylabel('True Positive Rate')
        plt.xlabel('False Positive Rate')
        plt.show()
    #Output
    def testClassification(self):
        self.Logistic()
        self.DT(False)
        self.RF()
       # self.SVC('linear')
        self.table()
```

In [146…

```
len(dataset)
```

Out[146…

```
15419
```

dataset shape : (15419, 76) Number of zeros : 14496 94.01387898047862 Number of ones : 923 5.98612101952137

In [147…

```
w0 = len(dataset) / (2 * 14496)
w1 = len(dataset) / (2 * 923)
```

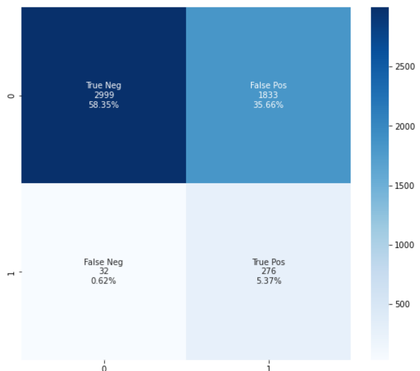
In [148…

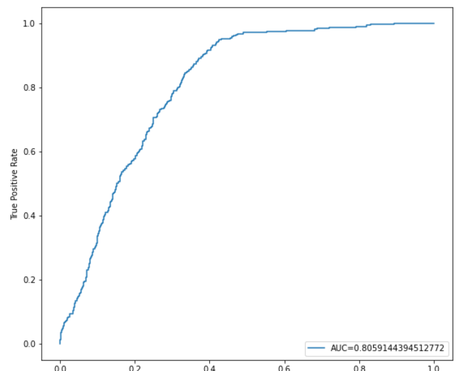
```
WeightClass = Models_Startified_WeightClass(dataset,'FraudFound_P',3,w0,w1)
```

In [149…

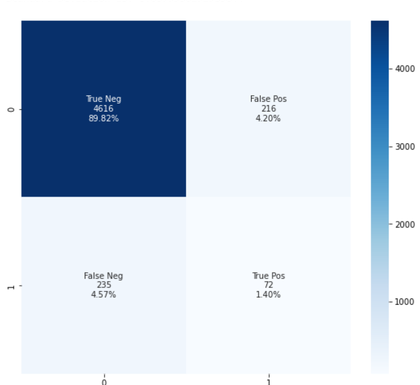
```
WeightClass.testClassification()
```

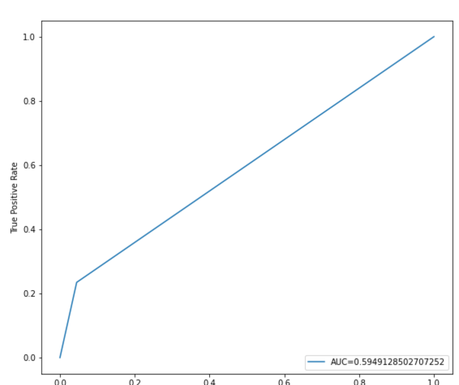
```
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
LogisticRegression.....................................

List of possible accuracy: dict_values([0.6371595330739299, 0.632295719844358, 0.6331971200622689])

Maximum Accuracy That can be obtained from this model is: 63.715953307392994 %

Minimum Accuracy: 63.22957198443579 %

Overall Accuracy: 63.42174576601855 %

Standard Deviation is: 0.0025874671772472026

List of possible F1-score: dict_values([0.22838229209764171, 0.2164179104477612, 0.21425593997498896])

Maximum F1-score That can be obtained from this model is: 22.838229209764172 %

Minimum F1-score: 21.42559399749896 %

Overall F1-score: 21.968538084013083 %

Standard Deviation is: 0.007608924243744882
```



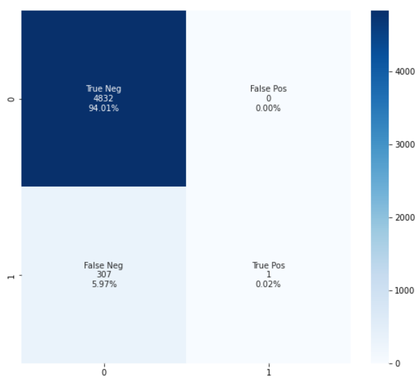


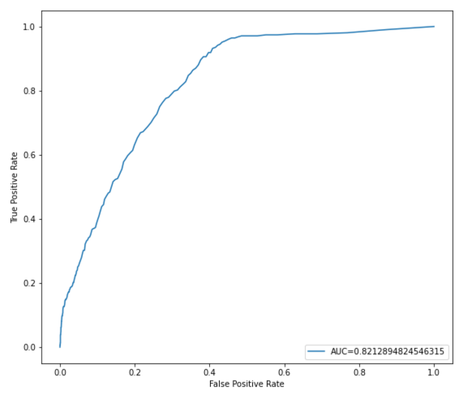

```
              precision    recall  f1-score   support

         Yes       0.99      0.62      0.76      4832
          No       0.13      0.90      0.23       308

    accuracy                           0.64      5140
   macro avg       0.56      0.76      0.50      5140
weighted avg       0.94      0.64      0.73      5140


DecisionTree.....................................

List of possible accuracy: dict_values([0.9023346303501946, 0.9071984435797665, 0.9122397353570734])

Maximum Accuracy That can be obtained from this model is: 91.22397353570733 %

Minimum Accuracy: 90.23346303501945 %

Overall Accuracy: 90.72576030956782 %

Standard Deviation is: 0.0049528174997233694

List of possible F1-score: dict_values([0.16611295681063123, 0.20100502512562815, 0.24201680672268908])

Maximum F1-score That can be obtained from this model is: 24.201680672268907 %

Minimum F1-score: 16.611295681063122 %

Overall F1-score: 20.30449295529828 %

Standard Deviation is: 0.0379930192985844
```






```
              precision    recall  f1-score   support

         Yes       0.95      0.96      0.95      4832
          No       0.25      0.23      0.24       307

    accuracy                           0.91      5139
   macro avg       0.60      0.59      0.60      5139
weighted avg       0.91      0.91      0.91      5139


RandomForest.....................................

List of possible accuracy: dict_values([0.9398832684824903, 0.940272373540856, 0.9400661607316598])

Maximum Accuracy That can be obtained from this model is: 94.0272373540856 %

Minimum Accuracy: 93.98832684824903 %

Overall Accuracy: 94.00739342516687 %

Standard Deviation is: 0.00019466896856317693

List of possible F1-score: dict_values([0.0, 0.006472491909385114, 0.0])

Maximum F1-score That can be obtained from this model is: 0.6472491909385114 %

Minimum F1-score: 0.0 %

Overall F1-score: 0.21574973031283715 %

Standard Deviation is: 0.00373689494621117
```






```
              precision    recall  f1-score   support

         Yes       0.94      1.00      0.97      4832
          No       1.00      0.00      0.01       308

    accuracy                           0.94      5140
   macro avg       0.97      0.50      0.49      5140
```

```
weighted avg       0.94      0.94      0.91      5140


F1-Score.........................................

                    0          1
0       DecisionTree  24.201681
1  LogisticRegression  22.838229
2       RandomForest   0.647249

Accuracy.........................................

                    0          1
0       RandomForest  94.027237
1       DecisionTree  91.223974
2  LogisticRegression  63.715953
```

Exercise 15

Implement a Bagging classifier from scratch. You can use sklearn for the base model. Test your model on the Penguins dataset. (Extra Point)

In [88]:
```
#Loading dataset
penguins_df = sns.load_dataset('penguins')
```

In [89]:
```
penguins_df
```

Out[89]:

	species	island	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g	sex
0	Adelie	Torgersen	39.1	18.7	181.0	3750.0	Male
1	Adelie	Torgersen	39.5	17.4	186.0	3800.0	Female
2	Adelie	Torgersen	40.3	18.0	195.0	3250.0	Female
3	Adelie	Torgersen	NaN	NaN	NaN	NaN	NaN
4	Adelie	Torgersen	36.7	19.3	193.0	3450.0	Female
...	...	...	...	...	...	...	...
339	Gentoo	Biscoe	NaN	NaN	NaN	NaN	NaN
340	Gentoo	Biscoe	46.8	14.3	215.0	4850.0	Female
341	Gentoo	Biscoe	50.4	15.7	222.0	5750.0	Male
342	Gentoo	Biscoe	45.2	14.8	212.0	5200.0	Female
343	Gentoo	Biscoe	49.9	16.1	213.0	5400.0	Male

344 rows × 7 columns

In [90]:
```
#Not related to target
penguins_df.drop('sex', inplace=True, axis=1)
```

In [91]:
```
penguins_df = pd.get_dummies(penguins_df, columns = ['island'])
```

In [92]:
```
penguins_df
```

Out[92]:

	species	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g	island_Biscoe	island_Dream	island_Torgersen
0	Adelie	39.1	18.7	181.0	3750.0	0	0	1
1	Adelie	39.5	17.4	186.0	3800.0	0	0	1
2	Adelie	40.3	18.0	195.0	3250.0	0	0	1
3	Adelie	NaN	NaN	NaN	NaN	0	0	1
4	Adelie	36.7	19.3	193.0	3450.0	0	0	1
...	...	...	...	...	...	...	...	...
339	Gentoo	NaN	NaN	NaN	NaN	1	0	0
340	Gentoo	46.8	14.3	215.0	4850.0	1	0	0
341	Gentoo	50.4	15.7	222.0	5750.0	1	0	0
342	Gentoo	45.2	14.8	212.0	5200.0	1	0	0
343	Gentoo	49.9	16.1	213.0	5400.0	1	0	0

344 rows × 8 columns

In [93]:
```
penguins_df['species'].unique()
```

Out[93]:
```
array(['Adelie', 'Chinstrap', 'Gentoo'], dtype=object)
```

In [76]:
```
penguins_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 344 entries, 0 to 343
Data columns (total 8 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   species            344 non-null    object
 1   bill_length_mm     342 non-null    float64
 2   bill_depth_mm      342 non-null    float64
 3   flipper_length_mm  342 non-null    float64
 4   body_mass_g        342 non-null    float64
 5   island_Biscoe      344 non-null    uint8
 6   island_Dream       344 non-null    uint8
 7   island_Torgersen   344 non-null    uint8
dtypes: float64(4), object(1), uint8(3)
memory usage: 14.6+ KB
```

In [77]:
```
penguins_df.dropna(inplace=True)
```

In [78]:
```
# Prepare the data X and Y (Based on species)
X = penguins_df.drop('species', axis=1).values
y = penguins_df['species'].values
```

In [81]:
```
# Encode categorical labels to numeric labels
label_encoder = LabelEncoder()
y = label_encoder.fit_transform(y)
```

In [82]:
```
# Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.15, random_state=42)
```

In [83]:
```
class BaggingClassifier(BaseEstimator, ClassifierMixin):
    def __init__(self, base_model=DecisionTreeClassifier(), n_estimators=10, max_samples=1.0):
        self.base_model = base_model
        self.n_estimators = n_estimators
        self.max_samples = max_samples
        self.estimators = []

    def fit(self, X, y):
        self.estimators = []
        for _ in range(self.n_estimators):
            X_resampled, y_resampled = resample(X, y, replace=True, n_samples=int(self.max_samples * X.shape[0]))
            estimator = self.base_model.fit(X_resampled, y_resampled)
            self.estimators.append(estimator)
        return self

    def predict(self, X):
        predictions = np.array([estimator.predict(X) for estimator in self.estimators], dtype=np.int64)
        majority_vote = np.apply_along_axis(lambda x: np.argmax(np.bincount(x)), axis=0, arr=predictions)
        return majority_vote
```

In [85]:
```
# Create and fit the Bagging classifier for decisontree
bagging = BaggingClassifier(base_model=DecisionTreeClassifier(), n_estimators=10, max_samples=0.8)
bagging.fit(X_train, y_train)
```

Out[85]:
```
BaggingClassifier
base_model: DecisionTreeClassifier
DecisionTreeClassifier
```

In [86]:
```
# Make predictions on the test set
predictions = bagging.predict(X_test)
```

In [ ]:
```
# Create and fit the Bagging classifier
bagging = BaggingClassifier(base_model=LogisticRegression(random_state=16, max_iter=1000), n_estimators=10, max_samples=0.8)
bagging.fit(X_train, y_train)
```

Evaluate model

In [ ]:
```
accuracy = accuracy_score(y_test, predictions)
print("Accuracy:", accuracy)
```

In [94]:
```
targetNames = ['Adelie', 'Chinstrap', 'Gentoo']
print(classification_report(y_test, predictions, target_names=targetNames,zero_division=1))
```

```
              precision    recall  f1-score   support

      Adelie       0.96      0.96      0.96        27
   Chinstrap       0.90      0.90      0.90        10
      Gentoo       1.00      1.00      1.00        15

    accuracy                           0.96        52
   macro avg       0.95      0.95      0.95        52
weighted avg       0.96      0.96      0.96        52
```